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COVARIANCE STRUCTURAL MODELS FOR MATHEMATICS ACHIEVEMENT AND PARTICIPATION: AN INVESTIGATION OF SEX DIFFERENCES AT THE LEVEL OF COLLEGE CALCULUS USING FACTORIAL MODELING

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BY

Thomas Patrick Dick

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To my daughter, Jean Clarice

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FOR MATHEMATICS ACHIEVEMENT AND PARTICIPATION:
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The purpose of this study was to develop covariance structural models that would explain, in terms of orthogonal latent variables, the correlations observed among mathematics achievement and participation measures and related cognitive and affective variables . A random sample of college calculus students (N = 268; 124 females and 144 males) was administered: 1) a battery of cognitive tests, including measures of spatial-visual ability, field independence/ field dependence, and logical reasoning; and 2) a battery of affective scales, including measures of attitude toward mathematics, confidence, perceived usefulness of mathematics, effectance motivation, and locus of control. Measures of previous academic achievement and participation in mathematics and science, and future academic plans, as well as achievement in the calculus course itself were recorded. The sample was then split into two equal-sized subsamples.

Using one subsample, a test of the hypothesis that males and females have the same covariance structure for these measures was performed. A significant difference ($p < .0001$) was found. Separate orthogonal factor models were developed for males and females based on these sample correlations. Sample correlations from the second subsample were used to evaluate the adequacy of the developed models by application of Factorial Modeling, a parameter estimation and confirmatory technique for orthogonal factor models. There was evidence of a reasonable fit for both models. Comparison of the two models revealed that academic experience and preparation were clearly the two most important factors in explaining variance in calculus achievement for both males and females, while the affective and cognitive factors contributed very little to variance in calculus achievement. The most profound differences between males and females were found in the affective domain, with the effects of perceived usefulness of mathematics on other affective variables being much stronger for males than females. Slight sex differences were found in the correlational structure of cognitive measures. The results implied that, at least at the level of college calculus, special programs aimed towards changing attitudes, or towards improving cognitive skills such as spatial ability, should not be expected to have a transfer effect to calculus achievement.

CHAPTER I

VARIABLES RELATED TO SEX DIFFERENCES IN MATHEMATICS ACHIEVEMENT AND PARTICIPATION-- NATURE, SCOPE, AND PURPOSE OF THE STUDY

Many factors have been suggested as being related to mathematics achievement. Biological, sociological, cognitive and affective psychological variables, as well as educational variables have been studied in attempts to better understand individual differences in the learning of mathematics (Fennema & Behr, 1980). Such research has relevance to the mathematics educator both in terms of predicting future mathematics achievement and deciding how best to intervene in order to improve mathematics learning.

The role these variables play in influencing academic choice, particularly the election of mathematics courses at the secondary and college levels, is also of interest. Observed group differences in mathematics achievement and participation between males and females and the disproportionately low representation of women in scientific and technical careers has prompted research aimed at finding the sources of these differences and explaining how they affect academic and career choices (Meece, Parsons, et al., 1982). This is of concern not only to the mathematics education community but also to researchers studying the intellectual and career development of women.

When measurements of a variable are found to be correlated with measurements of mathematics achievement, then that variable naturally comes under scrutiny as a possible source of individual differences observed in mathematics achievement. It is also natural to ask whether or not there are sex differences in the measures of this variable. If there are, then this variable might help account for or explain sex differences in mathematics achievement. Similarly, variables related to individual differences in mathematics participation are of interest in studying sex differences in mathematics participation. There is a clear connection between mathematics participation and career options, since training in mathematics is a prerequisite for entry into many technological and scientific fields. Students who choose not to pursue coursework in mathematics beyond general requirements effectively eliminate many career options for themselves. This has led some to refer to mathematics as a "critical filter" which prevents many students from pursuing and/or attaining certain career goals (Casserly & Rock, 1980; Sells, 1976). In general, women elect to take fewer mathematics courses than men, and hence women are underrepresented in those careers which make the most use of mathematics.

The tendency for women to elect fewer mathematics courses than men has been the focus of an increasing amount of research in the last decade (Armstrong, 1981; Boswell & Katz, 1980; Brush, 1979; Casserly & Rock, 1980; Fox, 1982; Fox, 1979; Hacket, 1981; Hacket & Betz, 1982; Lyons, 1980; Meece et al., 1982; Pedro et al., 1981; Pedro et al., 1980; Peng & Jaffe, 1979; Perl, 1982; Sherman, 1981; Sherman & Fennema, 1977; Steel & Wise, 1978; Wise et al., 1979; Wise, 1978). The goal of this research has been to provide a better understanding of the variables related to academic choice and mathematics achievement with respect to males and females. From this research one gathers that there are many variables correlated with mathematics achievement and participation. Some of these variables, such as genetic traits and certain social influences, are not reasonably within the scope of intervention efforts by mathematics educators. However, several variables could be subject to change through intervention.

In particular, there are several cognitive and affective psychological variables which are correlated with mathematics achievement and/or mathematics participation, and some of these may be alterable by actions taken by the mathematics educator. Some of the cognitive variables which have received special attention are: general intelligence, verbal and logical reasoning abilities, spatial ability, and cognitive styles such as field independence/ field dependence. Some of the affective variables which have been considered are: anxiety (which could be of many different types-- anxiety toward mathematics, state anxiety, general anxiety, test anxiety, facilitating anxiety, debilitating anxiety), confidence, effectance motivation, expectation of success, self-concept (both actual and ideal), alienation, extraversion-introversion, fear of success, self-esteem, the stereotyping of mathematics as a male domain, perceived usefulness of mathematics, and locus of control (causal attribution). Neither of these lists is intended to be exhaustive. Aiken has authored reviews on attitudes towards mathematics and other affective or non-intellective variables (1970a, 1970b, 1976) as well as on intellective variables and language factors (1971, 1972). Fennema has written papers summarizing the research into the possible influences cognitive and affective variables have in explaining individual differences (with Behr, 1980) and sex differences (1977) in mathematics achievement. For a review of the mathematics education research on spatial abilities see Bishop (1980). Witkin (1976) summarizes the research on and educational implications of cognitive styles. An excellent general review of the research on sex differences in mathematics achievement and academic choice is given in Meece, Parsons, et. al. (1982).

A theory which proposes to explain individual differences and, in particular, account for sex differences in mathematics achievement and participation must take into account these cognitive and affective variables. In developing such a theory, research can be aimed toward answering one or both of the following kinds of questions:

1) questions of source:

Are sex differences in mathematics achievement and/or participation primarily genetically sex-linked or due to differential environmental conditions and experiences? Are any sex differences in the related cognitive and affective variables due to genetic or environmental influences? When do these sex differences become apparent? Are the sex differences observed in any of these variables responsible for the sex differences observed in mathematics achievement and participation?

2) questions of structure:

What is the underlying structure of the correlations between these cognitive and affective variables and mathematics achievement and participation? Is this structure different for males and females? What are the relative strengths of the influences these variables have on each other and on mathematics achievement and participation?

Questions of source and structure are not unrelated. We will briefly review some of the research literature on the questions of source by considering some possible theoretical frameworks for understanding these questions. The evidence supporting these theories and their implications for research also will be discussed.

On the other hand, there seems to be little or no research which has attempted to study the structure of the correlations of a comprehensive set of cognitive and affective variables related to mathematics achievement and participation. What are needed are theoretical models which explain both the interrelationships among the relevant variables and their relationships to mathematics achievement and participation, in ways that could better guide subsequent research and intervention efforts.

The present study focuses on these questions of structure and makes an attempt to develop such models. We will review the research indicating which cognitive and affective variables hold the most promise in understanding both individual and sex differences in mathematics achievement and participation. The approach to understanding the correlational structure of measurements of these variables is that of causal modeling, which has been referred to as a "state-of-the-art" technique for observational educational studies (Cooley, in Jöreskog & Sörbom, 1979). But before discussing this any further, let us first take a look at some theories which attempt to explain the sources of sex differences in mathematics achievement and participation.

An Innate-Ability Theory

One theory which could explain both lower achievement and less participation in mathematics by women can be described very simply: women are innately inferior to men in mathematical ability. Therefore women do not score as high as men on measures of mathematics achievement. Naturally women would make academic choices which reflect their strengths, mathematical ability not being one of them. And, of course, a majority of women choose non-mathematically oriented careers for the same reason.

This argument implies that research on sex differences in mathematics achievement would best be directed toward finding exactly which biological variables account for these innate differences and outlining the developmental patterns describing how these differences emerge. Some biological variables which have been considered are brain organization or lateralization (Luchins, 1981; McGlone, 1980) and hormonal differences (Harris, 1975; Ware, 1982; Wittig & Petersen, 1979). But the research into the effects of these variables on mathematics achievement, especially in explaining sex differences, is far from conclusive (Harris, 1975; Luchins, 1981; Sherman, 1977). In reviewing the literature on possible biological sources of sex differences in mathematics achievement and course enrollment, Meece, Parsons, et al. (1982) noted that sex differences do not appear in any consistent pattern on either tests of quantitative skills or spatial skills prior to the tenth grade. Thus, if mathematics ability is indeed genetically sex-linked, then the differences between males and females develop around this time. In summary, this theory simply maintains that sex-linked differences in innate mathematical ability are major sources of observed differences in both mathematics achievement and participation.

A Differential Participation Theory

As just noted, consistent differences in mathematics achievement do not favor males until around the tenth grade. We also note that this is precisely the time when, for most students, mathematics courses become elective rather than required. Males choose more mathematically oriented careers than females. For example, during the fall 1983 semester at the University of New Hampshire, over 1200 students enrolled in freshman calculus. Approximately 45% of these students were women. However, only 25% of these women were enrolled in the College of Engineering and Physical Sciences, while 50% of the male calculus students were enrolled in this college.

A participation theory would maintain that there are no innate differences between males and females as far as mathematics ability is concerned, but that differences in course-taking behavior underlie differential achievement and higher level participation. Hence it is not an accidental coincidence that males start to score higher than females on measures of mathematics achievement at the upper secondary and college levels. Rather, it is the logical consequence of males participating in more mathematics-related activity than females.

Such an argument implies that research should focus on the sources of this differential course-taking behavior, since these same sources would automatically explain sex-differences in mathematics achievement. These sources might have little to do with mathematics achievement directly and may be predominantly socio-cultural in nature. One such class of variables which has been considered has been that of socializing influences. A socializer can be thought of as a person or experience which transmits cultural standards and expectations to an individual. Some researchers suggest that males and females are subjected to different social learning experiences. A comprehensive bibliography on the literature regarding sex role socialization has been prepared by Safilios-Rothschild (1979). Some of these different experiences may influence the perceived importance and utility of mathematics as well as the appropriateness of engaging in mathematics-related activity.

Other significant people in a child's academic environment, such as teachers and parents, may transmit their own stereotypes and attitudes about mathematics to the child. If these stereotypes and attitudes carry negative messages to girls and women about mathematics then this could explain differential participation in mathematics between males and females. This possibility has led to the construction of attitude measures which pertain specifically to these influences; for example, the Fennema-Sherman Mathematics Attitude Scales (Fennema & Sherman, 1976) include separate scales for measuring a child's perceptions of mother, father, and teacher.

The absence of female role models may in itself discourage women from pursuing mathematics-related activity (Brody & Fox, 1980; Tobin & Fox, 1980). There is data indicating that female student teachers and college-educated mothers hold more negative views of their mathematics abilities than their male counterparts (Aiken, 1970; Parsons, Adler, & Kaczala, in press, cited in Meece et al., 1982). The expectations significant others have and the different experiences they provide for children also have been investigated as sources for differing mathematics achievement (Meece, Parsons, et al., 1982). In summary, this theory maintains that males and females are subject to different environmental influences and hence choose to participate at different levels of mathematical activity such as academic course-taking. This differential participation in turn explains differential achievement.

Evidence Supporting Theories on Sources of Sex Differences

The two theories just discussed hold very different implications for research. What existing evidence is there to support each of these theories? If sex differences in mathematics achievement are still observed after controlling for mathematics coursework (either by experimental design or by statistically partialling out the amount of mathematics coursework taken) then one might feel that the first theory was the more plausible. If the sex differences disappeared after controlling for differential participation in mathematics then the second theory might seem more plausible. If a research study fails to control for differential participation then it would be difficult to use it to support either theory convincingly.

One can find evidence supporting both theories. Kirschner (1982) reviewed mathematics education research which indicated there were no inherent factors which prevent females from learning mathematics at the same level as males. Steel and Wise (1978) analyzed data from the large Project Talent data base and found that virtually all sex differences in mathematics achievement could be explained by sex differences in participation in high school mathematics.

However, other reviews of the research have indicated that sex-related differences exist even after controlling for mathematics background (Schonberger, 1978). Armstrong (1981) reported on the results of two national surveys which also indicated a persistence of sex differences in mathematics achievement even after different levels of mathematics participation were controlled. Benbow and Stanley's research with gifted children has often been cited in support of genetically sex-linked differences (see Benbow & Stanley, 1980, 1981, 1982a, 1982b, 1983). Their work involved students at the junior-high level, supposedly before mathematics participation had become differential. They suggested the mathematics achievement differences favoring males are profound enough that they may be at least partially genetically sex-linked. They also noted that these differences emerge earlier in gifted high math-ability students. Furthermore, they point out that the differences are most marked at the extreme upper end of the distribution.

Thus we can see that the "nature-nurture" debate is thriving with regards to sex differences in mathematics achievement. Certainly mathematics achievement is influenced by both genetic and environmental factors. Determining the relative strengths of these influences will keep many researchers busy for some time to come.

Cognitive and Affective Variables Related to Mathematics Achievement and Participation

One could complain that both of the two theories discussed above are too simplistic and that they ignore the influences of other relevant variables. For example, spatial ability is a cognitive variable that logically might have an influence on mathematics achievement and/or participation, given the geometric nature of some areas of mathematics. As noted before, differences favoring males on tests of spatial skills do not appear with any consistency until the tenth grade. This is the same level at which mathematics achievement differences appear consistently. Suppose that these sex differences in spatial ability are primarily genetically based. Since scores on spatial tests and scores on mathematics achievement tests are positively correlated (Armstrong, 1981; Burnett, et al., 1979; Fennema & Sherman, 1977,1978; Sherman, 1980), perhaps the sex differences in spatial ability account for the sex differences in mathematical ability. Or sex differences in spatial ability may make certain mathematics courses more appealing to men, which could result in differential course-taking and hence different achievement in mathematics. If this is true, then sex differences should disappear from mathematics achievement scores if we statistically partial out spatial skill differences.

Indeed, this has been the case (Burnett et al., 1979; Fennema & Sherman, 1977). However, this far from settles the issue. One can question the hypothesis that sex differences in spatial ability are primarily genetically based. De Wolf (1981) found that after statistically controlling for amount of coursework taken, sex differences disappeared on both tests of quantitative and spatial ability. There are several studies which have demonstrated that spatial skills, at least as they are measured on many current tests of spatial ability, can be improved through training (Burnett & Lane, 1980; Mundy, 1980). Sex differences in spatial skills seem to vary depending on previous experience with spatial activities (Burnett & Lane, 1980; Connor, et al., 1978; Connor, Serbin & Scharkman, 1977; Sherman, 1980). One might think that regardless of whether sex differences in spatial ability are innate, due to environmental influences, or a combination of both, they still hold the key to understanding sex differences in mathematics achievement. But Fennema and Sherman (1977) found that if they partialed out a set of scores representing attitudes toward mathematics on which sex differences were observed, then sex differences in mathematics achievement also disappeared. Such evidence suggests that just as convincing an argument could be made with mathematics attitudes in place of spatial ability.

It is equally unclear as to how other cognitive and affective variables relate to mathematics achievement and participation, especially in explaining sex differences. A clear pattern of sex differences does not appear in general intelligence as measured by various intelligence tests though females seem to score higher on measures of verbal ability, and males seem to score higher on measures of mathematical ability (Maccoby & Jacklin, 1974). Measures of verbal ability tend to correlate highly with measures of mathematical ability (Aiken, 1971) leading Fennema to hypothesize that there may be a verbal factor related to mathematics that has not been measured specifically by the usual tests of vocabularly, reading, etc. (Fennema, 1977).

In addition to spatial ability, cognitive style has been another cognitive variable of considerable interest in mathematics education research on individual and sex differences (Fennema & Behr, 1980; Fennema, 1977). Cognitive styles can be described as "characteristic modes of functioning" (Witkin, 1976) which influence perceptual and intellectual activity. Dimensions which have been identified include field independence/ field dependence, cognitive complexity/ simplicity, leveling/ sharpening, reflection/ impulsivity, risk taking/ cautiousness, constructed/ flexible control, strong/ weak automatization, conceptual/ perceptual-motor dominance, and converging/ diverging (Messick, 1976). These cognitive styles are generally regarded to be on bipolar continuums and do not reflect cognitive abilities as much as manners of cognitive functioning.

Field independence/ field dependence is the cognitive style which has received the most attention from mathematics education researchers, although Fennema and Behr (1980) indicate that reflection/ impulsivity also may be worth additional attention. Field independence/ field dependence is usually understood to be on an analytical/ global continuum of perception. Individuals near the field independent end of the continuum tend to be more analytical and better apt and able to break a perceptual situation into its component parts. On the other end of the continuum, field dependent persons tend to perceive situations globally and are less able to analyze them in terms of component parts. Most measures of field independence/ field dependence are tests which require an individual to "disembed" an object from its surroundings (examples: Rod and Frame Test, Embedded Figures Test; cf. Witkin et. al., 1971). Because a cognitive style is supposed to be revealed "throughout our perceptual and intellectual activities in a highly consistent and pervasive way" (Witkin, 1976, p. 39), the educational implications could be far-reaching. Witkin suggests that both achievement and educational-vocational interests are influenced, and hence

> the well-documented evidence of small but persistent sex differences in field-dependence-independence among adults suggests that it may be useful to examine the interests -choices-performance domains, in relation to cognitive style, for men and women separately.
> (Witkin et al., 1977, p. 51)

However, other researchers feel that field independence/field dependence does not merit much interest as a construct distinct from general intelligence. Horn (1976) goes as far as suggesting the theory be dropped. Fennema (1977) has suggested that the analytical/ global dichotomy may not be useful in understanding the learning of mathematics, but concentration on some kind of verbal/ spatial dimension might be a better focus for research. Because there is a spatial-visual aspect to many of the measures used as indicators of field independence/ field dependence there has been special interest to the relationship between it and spatial ability (Khoury & Behr, 1982; Satterly, 1976, 1979).

There is disagreement as to the role affective variables play in influencing mathematics achievement and participation. Aiken (1970a, 1976) noted low but significant positive correlations between attitude scores and mathematics achievement scores. Other reviewers conclude that there has been little research evidence convincing enough to indicate that attitudes are an important influence on mathematics achievement (Suydam & Weaver, 1975; Callahan & Glennon, 1975; cited in Fennema, 1977). It seems logical that attitudes might play a role in determining academic choices, and hence perhaps indirectly influence mathematics achievement. But we have the same problem as before in determining the direction of causal influence between these variables. That is, perhaps achievement and participation in mathematics influence attitudes toward mathematics, and not the other way around.

In her review, Fennema (1977) notes that there are flaws in using a global definition of "attitude toward mathematics" and that individuals can have different feelings toward different kinds of mathematics. This has led to the development of several different attitude scales in an attempt to measure several possibly different "dimensions" of attitudes toward mathematics. Some of these dimensions which appear to involve sex differences are: perceived usefulness of mathematics, stereotyping mathematics as a male domain, achievement motivation in mathematics, confidence and anxiety toward mathematics and effectance motivation (Fennema, 1977). Effectance motivation refers to feelings toward engaging in exploratory and experimenting behaviors.

Another affective variable which may be of interest is locus of control (Fennema, 1977). That is, where do individuals place responsibility for their successes or failures-- to themselves or to outside influences such as other people's actions or fate and luck? This construct is sometimes referred to as causal attribution and measures of it attempt to classify a person's attribution of cause either as external (to outside influences) or internal (to themselves). This classification is sometimes done separately for the attribution of cause to negative and positive events. Males and females do seem to differ on these measures with females more likely than males to attribute negative events to internal causes and positive events to external causes (Crandall et al., 1965; Messer, 1972). The educational implications are unclear but some mathematics education research has been directed towards locus of control as possibly relevant in explaining sex differences in mathematics achievement and participation (Brewer & Blum, 1979; Parsons, 1982; Williamson, 1980; Wolleat et al., 1980).

Causal Modeling as a Means to Understanding Correlational Structure

The relationships among these cognitive and affective variables and their effects on mathematical achievement and participation are complex and the need for further research is evident.

> Since a tremendously complex interplay of affective, educational, societal and possibly cognitive variables affect the decision to study mathematics, many different types of studies are necessary. (Fennema, 1977)

> ...a concensus has emerged that mathematics achievement is a complex phenomenon that is related to cognitive and affective variables, some of which are amenable to treatment (such as mathematics attitude and anxiety) while others are not (such as hereditary makeup). However, the concensus has been formed from piecemeal analyses, no one of which has combined all these variables into a single analysis.
> (Plake, Smith, Langley, & Kaplan, 1982)

Studies should involve as many of the potentially relevant variables as possible. One could attempt to employ an experiment of true factorial design so that effects of variables on mathematics achievement could be attributed unambiguously. However, the number of variables being considered would require us to make so many intrusions in the conventional educational setting that replication of the results might be extremely difficult, if not impossible. In other words, the price of internal validity may be too dear in terms of external validity.

An observational study which employs unobtrusive measures seems more appropriate if our goal is to better clarify the relationships between multiple variables in an educational environment. The question which remains is: What methodology is best for such explanatory observational studies?

Structural equation (causal) models were the subject of W. W. Cooley's address to the American Educational Research Association in 1978. In his concluding remarks he said:

> ...what is "the state-of-the-art" in the design and analysis of research studies involving relationships among variables? My sense of it is that, thanks to geneticists, economists, sociologists, and others, a very exciting "art form" exists that educational research has largely ignored.
>
> We must clearly produce more convincing causal models. The challenge is considerable, but the efforts will surely be more productive than continuing to conduct meaningless quasi-experiments, or averaging all of the t-tests they may have produced.
>
> (Cooley, pp. xxv,xxvi of Jöreskog and Sörbom, 1979)

Bentler echoed these sentiments when he focused his 1980 paper in the Annual Review of Psychology to

> ...the topic that I believe holds the greatest promise for furthering psychological science: multivariate analysis with latent variables and, more narrowly, linear structural equation (simultaneous equation, path analysis, structural relations, covariance structure) models with latent (unobserved, unmeasured) variables. (Bentler, 1980, p. 420)

In his address, Cooley outlined the key aspects of causal modeling studies. His discussion is summarized below using his outline of three topics (for the full address see the Introduction to Joreskog and Sorbom, 1979):

1) Sampling framework

The sampling framework affects the generalizability of the covariances we observe. As long as we draw a representative sample from a single well-defined population, then by measuring variables on that sample we can estimate the covariances among those variables in the population.

2) Theoretical model

The theoretical model describes the structure of the covariances in terms of causal influence. We cannot develop such a model on the basis of correlational information alone. Knowledge of the subject matter being investigated is crucial to building the model.

3) Statistical procedures

Statistical procedures are used to establish the plausibility of the theoretical model and estimating its parameters. Some procedures may be for exploratory purposes in developing the model and other procedures may be for confirmatory purposes.

It is perhaps more descriptive and accurate to refer to causal models as linear covariance structural equation models. They consist of sets of linear equations which explain the structure of and account for the covariances of a set of variables. These variables may be observed or latent (unobserved). These linear equations resemble linear regression equations. But in linear regression, the objective is to find the best predictors of individual variables in terms of linear combinations of other variables. In causal modeling, the objective is to find the most plausible explanation of the observed covariances in the entire set of variables. When educators and administrators make policy decisions that result in altering one variable, they can expect to see corresponding changes in several related variables. Good-fitting covariance structural models can help the decision-maker by demonstrating which of these changes will occur, and how strong these changes will be. When limited resources are available to those responsible for deciding how those resources should be allocated, it is imperative that the decision be made as intelligently as possible. Covariance structural models can form the basis for an informed decision.

Keeping the topics Cooley outlined in mind, the present study was designed. The population of interest in this study was that of calculus students at the college level. While college calculus students have had differing amounts of previous participation in mathematics, they all have a very full range of career options available to them in terms of technological and scientific careers.

The primary goal was to utilize causal modeling techniques to better understand differences between males and females with regards to mathematics achievement and participation, as well as with regards to related cognitive and affective variables. Of special concern in this study were the possibilities that males and females might have different covariance structures for variables measuring mathematics achievement, participation, and the related cognitive and affective constructs. If so, then causal modeling could shed light on the nature of those differences and point to the most fruitful directions for further research. If there are no differences in the covariance structures for males and females, then any sex differences could be understood in terms of the means of those variables. In this case, we could employ discriminant analysis to highlight the dimensions of greatest difference between males and females with respect to these variables, and then develop a single model for the covariances.

We decided to develop models that could be interpreted easily in terms of their explanations of the observed covariances. In the language of causal modeling, we concentrated on standardized orthogonal latent variable structural equation models. The measuring instruments chosen for the cognitive and affective variables and the statistical techniques used in analyzing the correlations to develop the models are discussed in detail in Chapter II. The statistical technique we used for confirmatory analysis of these models is called Factorial Modeling (FaM) and was developed by Paul Lohnes (1978) specifically for such models. Because causal modeling is a relatively new venture in educational research we will discuss the terminology and tools of causal modeling in more detail in Chapter III. Chapter IV will be devoted to a discussion of the technique of Factorial Modeling as a confirmatory tool for causal models.

Although the use of causal modeling is very promising for educational research, it is still in its early stages of use in that area. For this reason this study must be considered as an initial attempt to develop plausible models for the relationships between the many variables mentioned. It is hoped that this research study might result in a better understanding of variables influencing mathematics achievement and participation and perhaps focus more clearly our attention on those variables which account for individual and sex differences. Along the way, we also hope that the study serves as an example of the promise of covariance structural modeling in mathematics education research and, in particular, provides mathematics education researchers with an exposure to a tool of such methodology, namely Factorial Modeling.

CHAPTER II

RESEARCH PLAN, OBJECTIVES AND METHODS

The principal goal of the present study was to gain a better understanding of the structure of sex differences in mathematics achievement and participation through the development of covariance stuctural models. Of particular interest in this study were the contributions cognitive and affective variables related to mathematics achievement and participation make in explaining any sex differences. When one has gathered sample measurements of these variables, as well as sample measurements of mathematics achievement and participation, there are two natural types of statistics to consider when comparing males and females:

1) statistics of location

In other words, how do the sample mean vectors differ? Along what dimension is this difference most pronounced?

2) statistics of dispersion

How are the sample measurement vectors scattered about their respective means? What are the underlying sources of the observed variances and covariances?

Indeed, if it is reasonable to assume that our measured variables are from a multivariate normal distribution, then means, variances and covariances are precisely the sample statistics on which we should focus our attention.

When variables enjoy a multinormal distribution, discriminant analysis could be considered as a technique for finding the dimension along which the mean vectors for males and females are maximally separated. But discriminant analysis depends upon the additional assumption of equal variance-covariance matrices for the groups involved. If males and females do not have equal variances and covariances, then we could still employ discriminant analysis, while hoping that the procedure is robust enough to withstand the violation of this assumption. However, our attention should shift to these statistics of dispersion-- the variances and covariances. If we can develop models that explain the covariance structure of each group, then we have a vehicle for comparing males and females which can highlight differences that discriminant analysis would ignore. For this reason, the development of such models plays a central role in our approach to investigating sex differences in mathematics achievement and participation and related cognitive and affective variables. Factorial Modeling, a technique for fitting and confirming certain types of covariance structural models, is made use of in this regard.

While the list of variables considered in this study is not an exhaustive one, it is comprised of those variables of greatest practical interest to the mathematics educator in terms of individual and sex differences. By practical, we mean that these variables might be alterable through intervention. For example, the mathematics educator has little hope of changing biological factors even if they do play a role in influencing mathematics achievement and participation.

On the other hand, it may be possible to improve certain cognitive skills through training or alter attitudes through education.

In the rest of this chapter we discuss the particulars of our research plan, objectives, and methods, including the specific population under investigation, instruments employed to measure cognitive, affective, achievement, and participation variables, and stastistical tests and tools.

THE RESEARCH PLAN

A random sample of students (N = 268; 124 females and 144 males) was selected from the standard first-semester calculus class at the University of New Hampshire during the fall semester of the 1983-1984 academic year. This sample of students was administered various and multiple measures of the cognitive variables of spatial ability, field independence/ field dependence, and logical reasoning. All students in the class (approximately 1200), including this sample, were administered measures of affective variables such as attitudes toward mathematics and locus of control. In addition, all students filled out extensive background questionnaires reporting their previous participation in high school mathematics and science, verbal and quantitative SAT scores, and academic major. Finally, the achievement measures represented by the unit and final exams in the calculus course itself were recorded for the special sample. The reader can find the complete list of measures in Tables 1 through 4 on pages 39-41.

The sample of students selected for this study was split into two subsamples using stratified random sampling with respect to sex. Each subsample consisted of 62 females and 72 males. One subsample was designated for exploratory purposes. This sample was used to test the hypothesis that the variance-covariance matrices for the chosen measures were identical for males and females.

If this hypothesis was not rejected, then the underlying assumptions for a discriminant analysis would be met, and we could proceed to investigate differences in the means of the measures for males and females. If such an analysis further indicated that there were no significant differences in the means, then we could simply pool the two groups (subsample size of 134) and develop a single covariance structural model to explain the common structure of covariances for males and females. If the discriminant analysis indicated that there were significant differences in the means, then we could still develop a single covariance model based on the pooled variance-covariance matrix for males and females.

If the hypothesis of equal variance-covariance matrices for males and females was rejected, then we might still perform a discriminant analysis. However, we would want to be very cautious about interpreting the results of a discriminant analysis, since one of the underlying assumptions of such a procedure was violated. More importantly, rejection of this hypothesis would indicate that different covariance models should be developed for males and females to explain their different covariance structures.

Techniques such as principal component analysis, traditional factor analysis, and canonical correlation analysis, along with logical content considerations of the measures themselves, were used to develop the model or models indicated based on the sample covariance information provided by the first subsample. Initial fitting and parameter estimation for the models were accomplished using Factorial Modeling, which is discussed in greater detail in Chapter IV.

The second subsample was designated for confirmatory analysis of these models. No tests or exploratory analysis were performed on this second subsample. This subsample was used to obtain a second sample estimate of the variances and covariances of the measures employed in this study. These estimates were used to judge the adequacy of the developed models from the first subsample. The technique of Factorial Modeling played a central role in this confirmatory stage, by providing a way to estimate the parameters of a given model and any residual covariances not accounted for by the model. This confirmatory analysis also provided direction to further revision of the models for future research and analysis.

This study can be viewed as the initial step in the iterative process of model building and revision for the covariance structure of variables related to mathematics achievement and participation, specifically at the level of college calculus. The "split-sample" approach was used because of the lack of any already existing covariance models which attempt to explain the underlying structure of the covariances of such a comprehensive set of variables related to mathematics achievement and participation.

If a set of sample covariance estimates was used to help build a model, then it would be highly inappropriate to use the same sample to make a case for the model's adequacy in explaining the population covariances. Therefore, we used two samples-- one specifically for exploration and model development, and another for testing the adequacy of the developed models. We summarize our research objectives below.

RESEARCH OBJECTIVES

The specific objectives of this study were to answer the following questions:

* Are the covariance structures of the measured variables related to mathematics achievement and participation different for males and females?

If the covariance structures are <u>not</u> different, then we next try to answer:

* What is the common covariance structure in terms of a covariance structural model?

* How do the means of the measured variables differ for males and females?

If the covariance structures are different, we want to find

* How are differences in covariance structures reflected in terms of differences between the covariance structural models developed for males and females?

RESEARCH METHODS

Subjects

Subjects for the study were drawn from the first-semester calculus course at the University of New Hampshire (UNH) during the fall of the academic year 1983-84. UNH is a state school with a total enrollment of approximately 10,500. Approximately 1200 students enrolled in the course. Of these, approximately 45% were female. All were required to have completed three years of college preparatory mathematics including trigonometry. Every student in the College of Engineering and Physical Sciences is required to take calculus and almost every other college and department at UNH is represented. The 268 students selected for the sample receiving the additional cognitive measures were chosen randomly using the last digit of their social security numbers.

The Calculus Program at the University of New Hampshire

The first-semester calculus course at UNH is taught using a modified version of the Keller plan of personalized instruction. There are six large lecture sections from which the students may choose to attend. Students can choose to switch lecture sections without notice and can even attend several lectures in the same day. In addition, a tutorial room staffed by mathematics graduate students is open 30 hours a week for informal help sessions. Four days a week there are afternoon and evening problem sessions where solutions of selected homework exercises are presented.

The material covered in the course represents a standard course in differential and integral calculus. Swokowski's Calculus with Analytic Geometry is used as a text with chapters 1-8 being covered during the first semester. The topics covered include the basic material on differentiation and integration of algebraic, exponential and logarithmic functions with applications.

At the beginning of the semester an algebra and trigonometry pretest is administered to all students. It is used to determine which students need to review some precalculus mathematics. If a need for review is indicated for an individual student, then the student is required to make use of the individualized review materials at the UNH Mathematics Center and complete a review program specific to the student's needs by certain deadlines during the semester. The Mathematics Center is also available to anyone desiring review in algebra or trigonometry, or extra work on calculus materials.

Testing over the material covered in the calculus course is handled through a testing center. Each student enrolls in a testing laboratory as part of the course. This "lab" time consists of a weekly two-hour time block assigned to the student for test-taking during the semester. During the first two weeks of the semester, the student's lab is reserved for administration of pretests. For the remainder of the semester, the lab time is used for the unit exams for the calculus course.

The two-hour time period which makes up a student's lab time is partitioned into two parts. During the first hour the student is administered the exam. During the second hour the student has the exam graded while he/she observes. The student's mistakes are reviewed and discussed by the grader at this time. Because the grading process rarely takes the full second hour, this time also can be used to get feedback information from the students regarding the course, or to gather any other information which might be of interest in planning any course revisions for the future. In this way the administrators of the calculus course at UNH have been able to conduct an ongoing evaluation of the program over the years. For the purposes of the present study, this time was available to administer the additional cognitive and affective measures. Because of the history of the calculus program at UNH, the students saw these measures as a natural part of the course evaluation process. For this reason, the administration of additional cognitive and affective measurement instruments was accomplished with little intrusion to the normal course routine, and we were able to gather multiple unobtrusive measures of these variables.

A large pool of test questions has been developed for each of the four course units. Each of the unit tests consists of five problems selected from the pool of questions for that unit. Students are allowed to take each of the first three unit exams three times and the fourth unit exam twice. In all cases the score on the last exam stands as the students' score on that unit. The exams for any particular unit are designed to be parallel in content, but no individual student ever receives the same exam question twice.

The specific content of each unit is summarized below:

Unit 1: concept of limit and derivative; computation of limits and derivatives of rational functions and functions involving radicals and absolute values; chain, product, and quotient rules; implicit differentiation; higher derivatives; equations of tangent lines to curves.

Unit 2: critical numbers, relative and absolute extrema, inflection points, and concavity, and their role in curve sketching; the first and second derivative tests; asymptotes; max-min applications; related rates applications.

Unit 3: computation of antiderivatives with initial or boundary conditions; computation of definite and indefinite integrals of sums and products of basic terms of the form x^r (r a fraction or integer other than -1), and composites of such functions; computing areas of regions bounded by such functions; computing volumes of solids of revolution; computation of arc length, work done in simple physical operations, and the force exerted by a liquid.

Unit 4: laws of exponents and logarithms; analytic geometry of the conic sections (parabola, hyperbola, and ellipse); differentiation of functions involving logarithmic and exponential functions; logarithmic differentiation; antiderivatives of functions involving or resulting in logarithmic and exponential functions; applications involving logarithmic and exponential functions, such as exponential growth and decay.

At the end of the semester the students are administered a common final exam. This final exam consists of forty multiple-choice questions. The final exam is converted to a 100-point scale and the student's grade is then computed giving equal weight to each of the four unit exams and the final exam.

Measures employed in the study

Pretest measures and calculus achievement measures

All the students in the calculus course were administered a pretest covering the precalculus mathematics topics of algebra and trigonometry during the first week of the semester. The algebra pretest consisted of 25 multiple-choice items and the trigonometry pretest consisted of 16 multiple-choice items. These tests were developed by the Mathematical Association of America. While normally these measures are used for diagnostic purposes, they also could be considered as measures of previous achievement in precalculus mathematics for the purposes of this study. The students' scores on the unit exams and the final exam for the course itself were used as measures of current mathematics achievement. The unit exams consisted of five problems each, while the final exam consisted of 40 multiple-choice items covering the material in all four units. For the purposes of this study, the unit exams were measured on a 100-point scale, but the final exam was not converted to a 100-point scale. The raw 40-point scale was used for the measure of the calculus final exam.

Background questionnaire measures

All of the students filled out an extensive background information questionnaire in which they reported their scores on the quantitative and verbal sections of the Scholastic Aptitude Test, previous participation in high school mathematics and science courses, as well as their academic major. The SAT scores were used as measures of quantitative and verbal ability and achievement.

Three "previous participation" measures were derived from the high school coursework information. Participation in 1) precalculus mathematics (algebra, geometry, trigonometry, and any mathematics subjects which did not require calculus), 2) calculus, and 3) physical science (physics, chemistry, and computer science) were measured in semester grade points according to the scale: A = 5, B = 4, C = 3, D = 2, F = 1. For example, two semesters of "A" work and one semester of "B" work would result in 14 semester grade points. Two measures of "planned future participation" were derived from the student's indicated academic major. One measure was the number of college semester hours of mathematics (calculus level or above) required for the student's academic major. The other measure was the number of college semester hours of physical science and engineering required for the student's academic major. These measures provided convenient ways of quantifying previous and planned participation in mathematics, science and engineering for the purpose of comparing students' levels of participation and their academic choices.

Affective measures

In the first few weeks of the semester all students in the course were administered various mathematics attitude scales. The attitude measures used were Aiken's Revised Mathematics Attitude Scale (Aiken, 1963) and four of the Fennema-Sherman Mathematics Attitude Scales: Usefulness of Mathematics, Confidence in Learning Mathematics, Mathematics as a Male Domain, and Effectance Motivation in Mathematics (Fennema & Sherman, 1976). A few of the items on these scales were reworded slightly in order to make them more appropriate for college students.

All of these scales are Likert scales. They consist of a series of statements to which the individual responds with one of the following reactions: strongly agree, agree, undecided or neutral, disagree, or strongly disagree. Half of the statements are stated positively and half are stated negatively with regards to the attitude being measured. In the case of the scale Mathematics as a Male Domain, "positive" refers to the tendency not to stereotype mathematics as being more appropriate for males than females. The score on the scale is determined by assigning weights from 1 to 5 to each of the responses, with the direction depending on whether the statement is negative or positive, and then summing these weights. To control for course effects on these attitude measures, all students were administered any particular measure the same week of the semester. A separate "anxiety towards mathematics" scale was not administered since there is evidence that confidence and anxiety towards mathematics seem to reflect a single dimension (Fennema, 1977).

All of the above scales were further split into two subscales, corresponding to the "positive" and "negative" items. This was done for two reasons. First, this provided a convenient way to obtain multiple measurements of each possible affective variable. This consideration is important for developing latent variable covariance structural models, as discussed in the next chapter. Secondly, the correlation between the two subscales of any particular scale would provide a measure of how differently students respond to items worded positively or negatively.

Near the end of the semester a locus of control measure was administered to all of the students. In order to have a scale particularly appropriate to college calculus students, one was developed by revising several of the items from the Intellectual Achievement Responsibility Questionnaire developed by Crandall, Katkovsky, and Crandall (1965). This new scale consisted of 18 items; nine of the items were designed to measure attribution of cause to negative events and nine of the items concerned positive events. In each item, the individual chooses between an external and an internal cause for a given event. A score for either positive or negative events can be obtained by taking the number of items attributed to internal causes for the appropriate items. Thus, a high score represents an internal locus of control and a low score represents an external locus of control. Copies of this scale and the attitude scales used in the study can be found in the appendix.

Cognitive measures

The cognitive measures employed in this study were chosen to give multiple indications of spatial ability, field independence/ field dependence, and logical reasoning.

The measures of spatial ability chosen were a twelve-item version of the Visualization of Rotations section of the Purdue Spatial Visualization Tests (PSVR, 1976), and parts 1 and 2 of the Card Rotations test from the Ekstrom, French, Harman and Dermon Kit of Factor-Referenced Cognitive Tests (Ekstrom Kit, 1976).

The PSVR consists of items which require an individual to visualize the rotation of three-dimensional objects. Guay (1980) has argued that many of the other spatial ability tests used in educational research involve tasks that can be solved using analytical rather than spatial strategies. This would raise suspicions about the construct validity of such measures. The PSVR was designed to minimize the possibility that an analytic strategy could be used rather than a spatial strategy. The PSVR was administered to all students in the calculus course at the time of the pretest.

The Card Rotations test involves two-dimensional rotations. It is designed to be a measure of "spatial orientation", which is defined in the Ekstrom Kit as "the ability to perceive spatial patterns or to maintain orientation with respect to objects in space" (Ekstrom et al., 1976). The Card Rotations test was administered only to the special sample near the beginning of the semester, before any calculus tests were given.

At the same time as the administration of the Card Rotations test, the special sample was also administered tests representing multiple measurements of field independence/ field dependence and logical reasoning. Sections 2 and 3 of the Group Embedded Figures Test (GEFT, 1971) and parts 1 and 2 of the Hidden Patterns test from the Ekstrom Kit were chosen as measures of the cognitive style of field independence/ field dependence.

The GEFT was designed as an adaptation of the Embedded Figures Test (an individually administered measure of field independence/ field dependence) which would be appropriate for group testing (Witkin, Oltman, Raskin, and Karp, 1971). The first section of the GEFT is considered as a "warm-up" when the GEFT is administered to college students as it was in this study. The items on the GEFT require an individual to locate a simple plane figure embedded in a more complex plane figure. The Hidden Patterns test is a similar measure which requires an individual to note whether or not a given line pattern is embedded in another pattern. Ekstrom et al. (1976) refer to the Hidden Patterns test as a measure of a factor called "flexibility of closure", and note that while it appears related to field independence/field dependence, there is the possibility that they are not identical constructs.

The measures of logical reasoning chosen for this study also come from the Ekstrom Kit. These were parts 1 and 2 of the Nonsense Syllogisms test and parts 1 and 2 of the Diagramming Relationships test. The Nonsense Syllogisms test consists of syllogisms made up of nonsense statements, to control for individuals' previous experience with particular subject matter. The individual is required to judge the correctness of the reasoning displayed in each syllogism. A Diagramming Relationships test item requires the individual to select the correct Venn diagram representing the inclusion relationships for three given sets of things. For examples of items from the PSVR and the various tests chosen from the Ekstrom Kit, please refer to the appendix.

Because of the large number of measures employed in this study it would be helpful to have a system of abbreviations for future reference. These abbreviations are arranged in Tables 1 through 4 according to the source of the measures: pretest measures and calculus achievement measures, background questionnaire measures, affective measures, and cognitive measures.

Table 1. Pretest measures and calculus achievement measures

Abbreviation	Description
ALG	pretest items covering algebra (25 items)
TRIG	pretest items covering trigonometry (16 items)
UNIT1	calculus unit 1 exam score (out of 100 points)
UNIT2	calculus unit 2 exam score (out of 100 points)
UNIT3	calculus unit 3 exam score (out of 100 points)
UNIT4	calculus unit 4 exam score (out of 100 points)
FINAL	calculus final exam score (40 items)

Table 2. Measures from background questionnaire

Abbreviation	Description
QSAT	quantitative Scholastic Aptitude Test score
VSAT	verbal Scholastic Aptitude Test score
HSPC	semester grade points in precalculus mathematics (algebra, trigonometry, etc.)
HSCA	semester grade points in calculus
HSPS	semester grade points in physical science (physics, chemistry, and computer science)
RQMA	semester hours of mathematics (calculus and above) required for chosen academic major
RQPS	semester hours of physics, chemistry, computer science, and engineering required for chosen academic major

Table 3. Cognitive measures

Abbreviation	Description
GEFT2	section 2 score of Group Embedded Figures Test (9 items)
GEFT3	section 3 score of Group Embedded Figures Test (9 items)
HPT1	part 1 score of Hidden Patterns (200 items)
HPT2	part 2 score of Hidden Patterns (200 items)
NS1	part 1 score of Nonsense Syllogisms (15 items)
NS2	part 2 score of Nonsense Syllogisms (15 items)
DR1	part 1 score of Diagramming Relationships (15 items)
DR2	part 2 score of Diagramming Relationships (15 items)
CR1	part 1 score of Card Rotations (80 items)
CR2	part 2 score of Card Rotations (80 items)
PSVR	12-item version of the Visualization of Rotations section of the Purdue Spatial Visualization Tests

Table 4. Affective measures

Abbreviation	Description
AIKP	score on the 10 "positive" items from Aiken's Revised Mathematics Attitude Scale
AIKN	score on the 10 "negative" items from Aiken's Revised Mathematics Attitude Scale
CLMP	score on the 6 "positive" items from Fennema-Sherman Confidence in Learning Mathematics Scale
CLMN	score on the 6 "negative" items from Fennema-Sherman Confidence in Learning Mathematics Scale
PUMP	score on the 6 "positive" items from Fennema-Sherman Usefulness of Mathematics Scale
PUMN	score on the 6 "negative" items from Fennema-Sherman Usefulness of Mathematics Scale
SMDP	score on the 6 "positive" items from Fennema-Sherman Mathematics as a Male Domain Scale
SMDN	score on the 6 "negative" items from Fennema-Sherman Mathematics as a Male Domain Scale
EFMP	score on the 6 "positive" items from Fennema-Sherman Effectance Motivation in Mathematics Scale
EFMN	score on the 6 "negative" items from Fennema-Sherman Effectance Motivation in Mathematics Scale
LCIP	locus of control score for positive events (9 items; high scores represent internal locus and low scores represent external locus)
LCIN	locus of control score for negative events (9 items; high scores represent internal locus and low scores represent external locus)

Administration of the measures

Except for the locus of control measures and the calculus exams themselves, all of the measures were recorded or administered before or during the third week of the semester (the first week that the first unit calculus exam was administered) in order to minimize effects of the course itself on the measures. Many of the items on the locus of control measures were worded so that they referred to experiences of the student in the calculus course itself. It therefore made sense to postpone the administration of the locus of control measures until later in the semester. The exact schedule of administration follows:

Table 5. Schedule for measures

week 1: ALG, TRIG, QSAT, VSAT, HSPC, HSCA, HSPS, RQMA, RQPS, PSVR, AIKP, AIKN, CLMP, CLMN

week 2: GEFT2, GEFT3, HPT1, HPT2, NS1, NS2, DR1, DR2, CR1, CR2

week 3: PUMP, PUMN, SMDP, SMDN, EFMP, EFMN, UNIT1

weeks 4-12: UNIT1, UNIT2, UNIT3, and retakes of these exams

weeks 13-14: LCIP, LCIN, UNIT4, retakes of UNIT4

week 15: FINAL

In Table 6, we report the reliabilities for the algebra and trigonometry pretests, the final exam, and the cognitive and affective measures. If an estimate of reliablility could not be found in the literature, we computed Cronbach's coefficient alpha estimate of reliability using item data from our sample (N = 268). We indicate the source of each reliability estimate by either citing the appropriate literature reference, or by indicating "sample".

Table 6. Reliabilities of measures

Measure	Reliability	Source
ALG	.77	sample
TRIG	.63	sample
FINAL	.86	sample
PSVR	.83	sample (for 12-item version)
full version	.87, .89, .92	(KR-20 estimates; Guay, 1980)
GEFT2, GEFT3	.82	(Spearman-Brown estimate; Witkin, et. al., 1971)
HPT1, HPT2	.91 males .89 females	(11th & 12th graders; Ekstrom, et. al., 1976)
NS1, NS2	.57 males .46 females	(11th & 12th graders; Ekstrom, et. al., 1976)
DR1, DR2	.79	(naval recruits; Ekstrom, et. al., 1976)
CR1, CR2	.86 males .89 females	(11th & 12th graders; Ekstrom, et. al., 1976)
AIKP	.92	sample
AIKN	.92	sample
combined	.94	(Aiken & Dreger, 1961)
CLMP	.83	sample
CLMN	.86	sample
combined	.93	(Fennema & Sherman, 1976)
PUMP	.90	sample
PUMN	.90	sample
combined	.88	(Fennema & Sherman, 1976)
SMDP	.94	sample
SMDN	.91	sample
combined	.87	(Fennema & Sherman, 1976)
EFMP	.79	sample
EFMN	.86	sample
combined	.88	(Fennema & Sherman, 1976)
LCIP	.47	sample
LCIN	.44	sample

Statistical Tests and Methodology Used in the Study

Under the assumption of multivariate normality of the populations in question, there are several statistics available for testing the hypothesis:

$$H_0: \quad \Sigma_f = \Sigma_m$$

where Σ_f and Σ_m are the covariance matrices of females and males respectively for the measures just discussed. The alternative hypothesis in this case is that Σ_f and Σ_m are any two general positive definite matrices. Some of the tests available include Box's M statistic, Roy's largest root and others. See Morrison (1976) for details. Since the measures considered in this study are all sums, either of test item scores, semester grade points or semester hours, the assumption of multivariate normality does not appear at all unwarranted. Box's M statistic was chosen in this study because of its availability in the SPSS statistical software package.

After testing this hypothesis, we had two routes to take in terms of developing causal models. The two possibilities were:

H_0 rejected: A causal model should be developed for males and females separately based on a sample covariance matrix from each group.

H_0 held tenable: An additional hypothesis should be tested since the two groups are assumed to share the same covariance structure. That is,

$$H_0: \quad \mu_f = \mu_m$$

should be tested and a discriminant analysis should be performed. A single causal model should be developed based on the pooled sample estimate of the covariance matrix (if mean vectors do not differ) or based on the pooled covariance matrices (if mean vectors do differ).

In developing latent variable structural models based on a sample correlation or covariance matrix, some of the statistical tools utilized included canonical correlation analysis, principal component analylsis, and traditional factor analysis. Refer to Morrison (1976) for descriptions of each of these techniques. We note that multiple regression is actually just a special case of canonical correlation analysis and that canonical correlates and principal components can be found by extracting eigenvectors corresponding to matrices derived from the sample covariance matrix. All these techniques provide ways of exploring the structure underlying the covariances. Chapter III is devoted to an explanation of structural covariance models and related terminology.

Lohnes' Factorial Modeling technique was used to both estimate the parameters of the models and to check whether the models were supported by the data gathered from the second sample. Factorial Modeling (FaM) is a correlation matrix factoring procedure based on some of the techniques of Guttman (1940, 1944, 1952). It does not rely on maximum likelihood techniques, eigenvalue computation, or least squares calculations as do other procedures such as Jöreskog's LISREL or some of the exploratory techniques mentioned above. It is hoped that FaM allows for meaningful replication of results with models that are fitted to observational data gathered in educational settings. Factorial Modeling is discussed in Chapter IV.

As is often the case with certain measurements in educational research (such as attitude scales), we had to deal with the problem of missing observations. In the present study, we had complete data from the pretests, unit exams, final exam, cognitive measures, and background questionnaire for all students in our sample. However, even after follow-up mailing and telephoning, we found that 5 to 15 per cent of the sample did not provide a response on any particular affective measure.

Statistical software packages such as SPSS often allow two options for computing covariance matrices when some components of the response vector are missing for some of the individuals. One option is to compute the sample covariance matrix using only those individuals with full response vectors. The other option is to compute each entry of the covariance matrix (i.e. each covariance between two responses) based on all individuals with the responses required for that particular entry. Neither option made much sense in this study. Because of the number of affective scales employed, the first option would have resulted in a small, possibly nonrepresentative sample on which to base results. The second option results in a covariance matrix made of entries based on several different samples, while the test statistic used in this study (Box's M) is based on the assumption that the matrix of covariances comes from a single sample.

We decided to use a procedure discussed by Anderson (1957) for computing maximum likelihood estimates of the means and covariances which utilizes all available responses from subjects in the sample. We refer the reader to the original article by Anderson (1957) or to the discussion of the method in Morrison (1976) for the details and formulas involved in the procedure. For a discussion of the most efficient ways to carry out these computations, see Rubin (1974).

In summary, our approach to the investigation of sex differences in mathematics achievement and participation was to focus primary attention on possible differences in the covariance structures of the relevant measures for males and females. In the multivariate normal setting, many tests of equality for mean vectors require equal variance-covariance matrices of the groups involved, as does discriminant analysis. Hence, measures of dispersion, not location, demand our initial attention. The separate covariance structural models developed for males and females in this study provide a rich means of comparison for the investigation of sex differences.

The language and tools of causal models are discussed in the next chapter to provide the reader with some background in this area. Factorial Modeling, a specific tool of causal modeling parameter estimation and fitting of which we make much use, is discussed in Chapter IV. We hope that this study might alert the reader to the possibilities of applying this methodology in educational research.

CHAPTER III

CAUSAL MODELING

The purpose of this chapter is to discuss the basics of causal modeling and the tools of linear structural equations and path analysis while establishing notation and terminology for subsequent discussion. A general reference on causal modeling is provided by Kenny (1979). An overview of causal modeling with latent variables which includes an excellent bibliography is provided by Bentler (1980). Jöreskog and Sörbom's <u>LISREL VI Manual</u> provides both examples of causal modeling and uses of the statistical technique of maximum likelihood factor analysis.

Parameter Notation

Let X_1 and X_2 denote random variables measured on a given population. Let μ_1 and μ_2 denote the respective population means of these variables. We will use the following notations:

$$Cov(X_1,X_2) = \underline{\text{covariance}} \text{ of } X_1 \text{ and } X_2$$

i.e.,

$$Cov(X_1,X_2) = (1/N) \sum (X_1 - \mu_1)(X_2 - \mu_2),$$

where the summation is over all N members of the population.

Thus,

$$Cov(X_1,X_1) = Var(X_1) = \underline{\text{variance}} \text{ of } X_1$$

$$= (1/\sum (X_1 - \mu_1)^2 \mu_1)^2$$

The <u>correlation</u> between X_1 and X_2 is defined as

$$p_{12} = Cov(X_1,X_2)/ \sqrt{Var(X_1)Var(X_2)}$$

We can <u>standardize</u> the variable X_1 by subtracting its mean and then dividing by its <u>standard deviation</u>, i.e., $(X_1 - \mu_1)/\sqrt{\mathrm{Var}(X_1)}$ is a standardized variable. Standardized variables have mean zero and unit variance and the covariance between any two of them is the same as their correlation.

Causal Models and Structural Equations

The objective of causal modeling is to explain both causal and non-causal influences between variables. For example, suppose two variables X_1 and X_2 are positively correlated. There could be various explanations for this correlation. Is there a causal relationship between the variables? If so, what is its direction (i.e., does X_1 cause X_2 or vice-versa)? Or is there a third variable X_3 which causes both X_1 and X_2, making the relationship between them a spurious one? Causal models attempt to answer such questions by specifying causal relationships between the variables included in the model and the directions of those relationships. Moreover, a causal model seeks to describe the relative magnitudes of these causal influences among variables in such a way that the covariances and variances are accounted for. For completeness of the model, covariances between variables for which no causal statement is made are also stated so that the complete set of variances and covariances may be recovered from the model. It is for these reasons that it might be more appropriate to refer to causal models as covariance structural models.

If the common assumptions of linearity and additivity of effects are adopted then a causal model can be described through a set of structural equations. A structural equation is a linear equation which expresses one variable, the effect, in terms of one or more other variables, the causes. Thus a linear structural equation resembles a linear regression equation with the effect playing the role of the dependent variable and the causes playing the roles of the independent variables. To emphasize the distinction between structural and regression equations we will follow Kenny's (1979) use of terminology and refer to effects as endogenous variables and to causes as exogenous variables.

For example, suppose we have measured variables X_1, X_2, X_3, and X_4 that are standard in the sense of common mean zero and unit variance. A model might stipulate that

$$X_1 = aX_2 + bX_3$$

$$X_2 = cX_3 + dX_4$$

$$p_{34} = p$$

where p is the correlation stated between X_3 and X_4 since the causes of these variables are not described by the model.

The structural parameters of this model are the structural coefficients (or path coefficients) a, b, c, d along with the stated correlation p. In this model X_1 is purely endogenous; X_3 and X_4 are purely exogenous; X_2 is both an endogenous and exogenous variable. The model states that X_1 is completely determined by X_2 and X_3 while X_2 is determined by X_3 and X_4. The model makes no statement regarding the causes of X_3 and X_4. In interpreting the structural equations, the model indicates that if X_3 is held fixed and X_2 is increased by one standard deviation, then one will see a corresponding increase in X_1 of (a) standard deviations. However, if X_4 is held fixed and X_3 is increased by one standard deviation, then X_2 will increase by (b + ac) standard deviations (due to increases in both X_2 and X_3).

It does not make sense to solve a structural equation for one of the exogenous variables as if it were simply an algebraic equation. This becomes clear if we attach some actual meanings to the variables in the the first equation of our example. If X_1 represents a student's college calculus grade, while X_2 represents high school mathematics grade average and X_3 represents IQ, then it would not make sense to solve for X_2 in terms of X_1 and X_3 because of temporal considerations. In other words, a structural equation carries with it not only a mathematical meaning, but also a causal interpretation for the variables involved.

Recovering Correlational Information from Structural Parameters

With a standardized causal model, i.e., one that involves standardized variables like the example discussed above, it is not a difficult matter to determine the correlations between the variables from the structural equations. The main property of covariances that we use is that of bilinearity. That is, for any three random variables X, Y, and Z, and real numbers r and s, we have:

$$Cov(rX + sY,Z) = rCov(X,Z) + sCov(Y,Z)$$

$$Cov(X,rY + sZ) = rCov(X,Y) + sCov(X,Z)$$

Let us illustrate how we use this property to determine correlations. In the example above we would note from the first equation

$$X_1 = aX_2 + bX_3$$

that

$$1 = Var(X_1) = Cov(X_1,X_1) = Cov(X_1,aX_2 + bX_3)$$

$$= aCov(X_1,X_2) + bCov(X_1,X_3) = ap_{12} + bp_{13}$$

by using the bilinearity of covariances and the standardization assumptions. Similarly, we have from the second equation that

$$1 = cp_{23} + dp_{24}.$$

All of the six distinct correlations can be expressed in terms of the structural parameters. We have, using $p_{34} = p$,

$$p_{12} = Cov(X_1,X_2) = Cov(aX_2 + bX_3,X_2) = a + bp_{23},$$

$$p_{13} = Cov(X_1,X_3) = Cov(aX_2 + bX_3,X_3) = ap_{23} + b,$$

$$p_{14} = Cov(X_1,X_4) = Cov(aX_2 + bX_3,X_4) = ap_{24} + bp,$$

$$p_{23} = Cov(X_2,X_3) = Cov(cX_3 + dX_4,X_3) = c + dp,$$

$$p_{24} = Cov(X_2,X_4) = Cov(cX_3 + dX_4,X_4) = cp + d,$$

$$p_{34} = Cov(X_3,X_4) = p.$$

We see that p_{23}, p_{24}, and p_{34} are given explicitly in terms of the structural parameters. By substituting these expressions into those for p_{12}, p_{13}, and p_{14}, we obtain

$$p_{12} = a + bc + bdp$$

$$p_{13} = ac + adp + b$$

$$p_{14} = acp + ad + bp$$

and thus all the correlations are given explicitly in terms of the structural parameters.

Determining Sample Estimates of Structural Parameters

On the other hand, if we know the values of the correlations between the variables in a standardized model we can use the structural equations to solve for the structural parameters. By solving the expressions for the correlations above as simultaneous systems of equations in the unknown parameters a, b, c, d, and p we obtain

$$a = (p_{12} - p_{13}p_{23})/(1 - p_{23}^2),$$

$$b = (p_{13} - p_{12}p_{23})/(1 - p_{23}^2),$$

$$c = (p_{23} - p_{24}p_{34})/(1 - p_{34}^2),$$

$$d = (p_{24} - p_{24}p_{23})/(1 - p_{34}^2),$$

$$p = p_{34}.$$

In this way we can determine sample estimates of the structural parameters by using these equations and sample estimates of the correlations. Furthermore, by substituting these expressions into the first two equations derived above, namely

$$1 = ap_{12} + bp_{13},$$

and

$$1 = cp_{23} + dp_{24},$$

we obtain the following two equations:

$$1 = p_{12}^2 + p_{13}^2 + p_{23}^2 - 2p_{12}p_{13}p_{23},$$

and

$$1 = p_{23}^2 + p_{24}^2 + p_{34}^2 - 2p_{23}p_{24}p_{34}.$$

Together these give us

$$p_{23}=(p_{12}^2+p_{13}^2-p_{24}^2-p_{34}^2)/(2(p_{12}p_{13}-p_{24}p_{34})).$$

The reader can check that there are also two other similar restrictions on the correlations due to the structural equations.

In other words, not any set of correlations will "fit" this model. This is due to the fact that we have six correlations but our model only involves five parameters. Such restrictions allow us to test whether or not sample data support the model. If the sample correlations satisfy the restrictions placed on them by the model, however, this does <u>not</u> mean that our model is correct. It only indicates that the data are compatible with the structural equations. Indeed, many models can be supported by the same set of data. The worth of a model cannot be ascertained by just correlational information. The reasonableness of the causal statements made by the model must be judged in light of the existing substantive knowledge of the variables involved. Thus causal models are evaluated both through statistical and theoretical considerations.

Disturbance Terms

Certainly the model discussed above is unrealistic for most cases of variables involved in educational research. The model claims that the variable X_1 is completely determined by X_2 and X_3. It is rare that we find that we can account for 100% of the variance in a measured variable in terms of the variance of other measured variables. There may be variance specific to that variable alone, measurement error in the instruments used, or influences of other variables not considered in the model. Indeed, Kenny suggests that when causal models involve variables of human behavior "a good rule of thumb is that one is fooling oneself if more than 50% of the variance is predicted" (p. 9, Kenny, 1979).

This leads to the inclusion of additional unmeasured variables in causal models. These variables are referred to as disturbance terms. Disturbance terms represent the sources of all unexplained variance in the endogenous variables.

As an example we will consider the following model which is a slight modification of our previous example:

$$X_1 = aX_2 + bX_3 + e_1U_1$$

$$X_2 = cX_3 + dX_4 + e_2U_2$$

with $p_{34} = p$ as before; U_1 is uncorrelated with U_2, X_2, X_3, and X_4; U_2 is uncorrelated with X_3 and X_4, as well as with U_1.

Note that the model now includes two unmeasured purely exogenous variables U_1 and U_2. The additional parameters in the model can be solved for under the standardization assumption. For example, from the second structural equation we have:

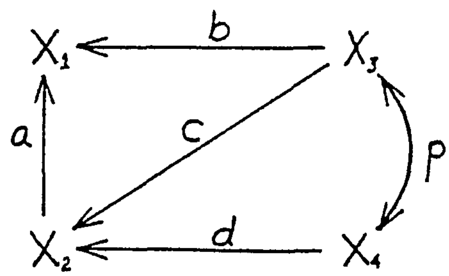
$$\begin{aligned} 1 = \mathrm{Var}(X_2) &= \mathrm{Cov}(cX_3+dX_4+e_2U_2, cX_3+dX_4+e_2U_2) \\ &= c^2 + d^2 + 2cdp + e_2^2 \end{aligned}$$

hence, $e_2^2 = 1 - (c^2 + d^2 + 2cdp)$ and if we assume that U_2 is positively correlated with X_2 then we may take e_2 to be the positive square root of this quantity. Similarly we may solve for e_1. By substituting sample estimates of the correlations into these expressions we may obtain numerical estimates of all of the structural parameters. Disturbance terms may be uncorrelated as they are in this example. It is common to think of the disturbance terms as representing pure error terms and error terms are often assumed to be uncorrelated. But disturbance terms may well be correlated. Indeed, this could be the source behind an ill "fit" of a model to data if the model mistakenly hypothesizes that disturbance terms are uncorrelated when they are not.

Path Analysis

Interpretation of causal models can be aided through the use of a path diagram. A path diagram consists of a symbol for each variable involved in the model. For a structural equation, an arrow is drawn from each exogenous variable pointing to the endogenous variable. These arrows are labelled with the path coefficients. For any stated correlation between two purely exogenous variables, a double-headed arrow is drawn between those variables labelled with the stated correlation. If that correlation happens to be zero, then that arrow may be deleted from the diagram.

For example, a path diagram representing our first example would look like:



From this diagram we can recover both of the structural equations,

$$X_1 = aX_2 + bX_3,$$

$$X_2 = cX_3 + dX_4,$$

and the correlation between the purely exogenous variables,

$$p_{34} = p.$$

Through the use of path analysis one can more easily recover the correlations between the variables. The main tools of path analysis are called:

1) the first law of path analysis,

and

2) the tracing rule.

Here we are following the terminology used by Kenny (1979), and we note that these two tools are equivalent for models which do not include reciprocal cause and effect relationships (i.e., of the sort: X causes Y and Y directly or indirectly causes X). These rules are simply restatements of covariance algebra in terms of the path diagram. In order to describe these tools we will need to introduce some more notation.

Denote by s_{ij} the path coefficient on an arrow from X_j to X_i and by p_{ij} the correlation between X_i and X_j. Then the first law states that

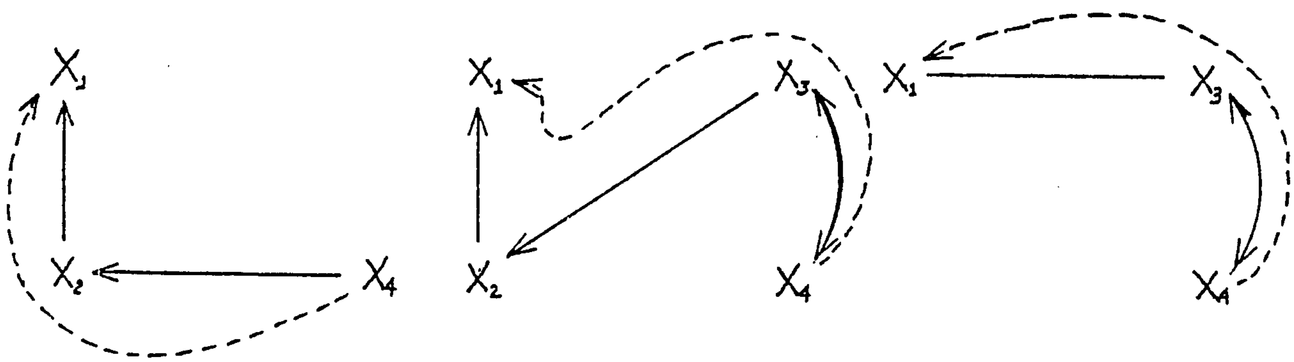
$$p_{ij} = \sum_k s_{ik}p_{kj}$$

where k runs over the indexes of all variables X_k which are causes of X_i.

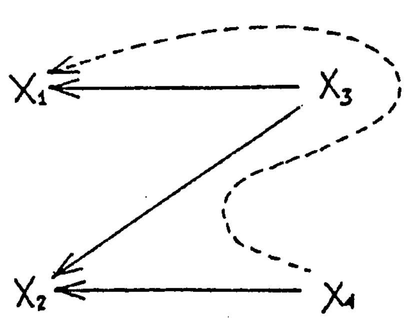
Thus, from our path diagram above and the first law, we would conclude that $p_{12} = ap_{22} + bp_{32} \doteq a + bp_{23}$, just as we obtained before.

For the tracing rule we need to define first a <u>tracing</u> from X_i to X_j as any route followed in the path diagram from X_i to X_j which does not enter any variable more than once and does not both enter and leave the same variable through an arrowhead.

For example, in the path diagram above there are three tracings from X_4 to X_1:



However, the following route would not be a tracing from X_4 to X_1, since X_2 is both entered and left through an arrowhead:



CORRELATION MATRIX FOR FEMALES

VARIATE	HPT2	VSAT	NS1	NS2	DR1	DR2	LCIP	LCIN
HSPC	-0.091	0.077	-0.031	0.026	-0.039	0.177	-0.266	-0.168
HSCA	-0.108	-0.017	0.141	-0.015	-0.101	-0.070	0.020	-0.066
HSPS	0.125	0.050	0.118	0.320	0.227	0.327	0.068	-0.163
QSAT	0.079	0.387	0.222	0.204	0.295	0.249	0.029	-0.069
ALG	0.163	0.093	0.137	0.022	0.046	-0.013	0.013	-0.289
TRIG	0.023	-0.112	0.127	0.060	-0.197	-0.250	0.113	0.133
SMDP	0.146	0.186	0.040	0.019	0.019	0.204	0.082	-0.041
SMDN	0.091	0.167	-0.109	0.066	0.061	0.019	0.173	0.102
PUMP	0.055	0.049	0.049	0.177	-0.081	0.039	0.142	0.031
PUMN	0.254	0.117	-0.053	-0.071	-0.111	-0.007	0.142	-0.004
ROMA	0.079	-0.085	-0.046	0.152	0.001	-0.003	-0.190	-0.032
ROPS	0.042	0.005	-0.039	0.123	-0.005	-0.063	0.133	0.038
AIKP	0.099	-0.177	-0.079	-0.105	0.036	0.134	0.149	-0.222
AIKN	0.184	-0.141	-0.087	-0.094	0.066	0.103	0.171	-0.129
CLMP	0.274	-0.003	-0.018	0.107	-0.054	0.090	0.218	-0.035
CLMN	0.188	-0.053	-0.079	-0.027	0.026	0.040	0.264	-0.046
EFMP	0.052	0.110	0.121	-0.078	0.182	0.181	0.428	-0.152
EFMN	0.135	0.199	-0.115	-0.105	0.135	0.165	0.296	-0.088
CR1	0.422	-0.152	-0.056	0.088	0.157	0.211	0.161	0.153
CR2	0.316	0.009	0.015	0.080	0.200	0.302	0.138	-0.041
PSVR	0.169	0.054	0.148	0.001	0.274	0.264	-0.096	-0.231
GEFT2	0.196	0.076	0.129	0.104	0.196	0.234	-0.138	-0.239
GEFT3	0.078	0.097	0.081	0.103	-0.053	0.037	-0.228	-0.403
HPT1	0.693	0.038	-0.061	0.112	0.003	0.195	0.086	-0.043
HPT2	1.000	0.038	-0.105	-0.070	-0.007	0.230	0.224	0.246
VSAT	0.038	1.000	0.248	0.349	0.311	0.266	-0.001	0.118
NS1	-0.105	0.248	1.000	0.312	0.107	0.064	0.284	-0.018
NS2	-0.070	0.349	0.312	1.000	0.115	0.037	0.204	0.278
DR1	-0.007	0.311	0.107	0.115	1.000	0.642	0.125	0.037
DR2	0.230	0.266	0.064	0.037	0.642	1.000	0.017	-0.188
LCIP	0.224	-0.001	0.284	0.204	0.125	0.017	1.000	0.282
LCIN	0.246	0.118	-0.018	0.278	0.037	-0.188	0.282	1.000
UNIT1	0.168	-0.010	0.006	-0.009	-0.164	-0.081	0.166	0.373
UNIT2	0.078	0.011	0.167	0.203	-0.010	0.092	0.193	0.158
UNIT3	-0.095	-0.008	0.138	0.138	-0.151	-0.167	0.129	0.158
UNIT4	-0.003	-0.002	0.162	0.239	-0.173	0.048	0.211	0.005
FINAL	-0.014	0.140	0.205	0.227	-0.058	0.038	0.149	-0.063

CORRELATION MATRIX FOR FEMALES

VARIATE	UNIT1	UNIT2	UNIT3	UNIT4	FINAL
HSPC	-0.046	0.181	0.223	0.244	0.269
HSCA	0.205	0.230	0.173	0.253	0.434
HSPS	-0.046	0.295	0.055	0.347	0.363
QSAT	0.089	0.218	0.095	0.226	0.351
ALG	0.242	0.347	0.355	0.404	0.440
TRIG	0.202	0.368	0.321	0.381	0.280
SMDP	-0.122	0.134	-0.074	-0.061	0.031
SMDN	0.151	0.176	0.033	-0.035	0.075
PUMP	0.332	0.397	0.335	0.342	0.478
PUMN	0.281	0.331	0.075	0.131	0.282
ROMA	0.200	0.292	0.187	0.179	0.287
RQPS	0.135	0.331	0.236	0.308	0.340
AIKP	0.083	0.214	0.032	0.238	0.212
AIKN	0.085	0.256	0.024	0.228	0.246
CLMP	0.265	0.249	0.180	0.320	0.418
CLMN	0.189	0.270	0.076	0.278	0.356
EFMP	0.110	0.259	0.192	0.248	0.319
EFMN	0.127	0.174	-0.005	0.096	0.216
CR1	0.103	0.053	0.099	0.155	0.010
CR2	-0.031	0.120	0.130	0.197	0.053
PSVR	0.129	-0.022	0.043	0.048	0.077
GEFT2	-0.123	-0.042	-0.091	0.081	-0.050
GEFT3	-0.138	-0.009	-0.022	0.146	-0.011
HPT1	-0.033	0.042	-0.047	0.047	0.005
HPT2	0.168	0.078	-0.095	-0.003	-0.014
VSAT	-0.010	0.011	-0.008	-0.002	0.140
NS1	0.006	0.167	0.138	0.162	0.205
NS2	-0.009	0.203	0.138	0.239	0.227
DR1	-0.164	-0.010	-0.151	-0.173	-0.058
DR2	-0.081	0.092	-0.167	0.048	0.038
LCIP	0.166	0.193	0.129	0.211	0.149
LCIN	0.373	0.158	0.158	0.005	-0.063
UNIT1	1.000	0.496	0.563	0.470	0.525
UNIT2	0.496	1.000	0.699	0.722	0.719
UNIT3	0.563	0.699	1.000	0.811	0.753
UNIT4	0.470	0.722	0.811	1.000	0.773
FINAL	0.525	0.719	0.753	0.773	1.000

CORRELATION MATRIX FOR MALES

VARIATE	HSPC	HSCA	HSPS	QSAT	ALG	TRIG	SMDP	SMDN
HSPC	1.000	0.180	0.113	0.258	0.152	0.172	0.016	0.152
HSCA	0.180	1.000	0.249	0.297	0.293	0.227	0.043	0.019
HSPS	0.113	0.249	1.000	0.340	0.241	0.244	-0.197	-0.162
QSAT	0.258	0.297	0.340	1.000	0.494	0.237	-0.117	-0.070
ALG	0.152	0.293	0.241	0.494	1.000	0.474	-0.027	0.043
TRIG	0.172	0.227	0.244	0.237	0.474	1.000	0.066	0.179
SMDP	0.016	0.043	-0.197	-0.117	-0.027	0.066	1.000	0.523
SMDN	0.152	0.019	-0.162	-0.070	0.043	0.179	0.523	1.000
PUMP	0.294	0.282	0.210	0.372	0.363	0.244	0.036	0.224
PUMN	0.167	0.340	0.138	0.405	0.286	0.260	-0.059	0.305
RQMA	0.249	0.296	0.061	0.222	0.321	0.371	-0.075	0.187
RQPS	0.132	0.273	0.284	0.394	0.360	0.236	0.004	-0.012
AIKP	0.306	0.208	0.280	0.309	0.358	0.429	-0.132	0.066
AIKN	0.258	0.184	0.260	0.317	0.352	0.463	-0.149	0.063
CLMP	0.354	0.224	0.118	0.264	0.280	0.400	-0.167	0.105
CLMN	0.234	0.264	0.148	0.385	0.401	0.451	-0.105	0.093
EFMP	0.404	0.185	0.231	0.171	0.252	0.382	0.073	0.374
EFMN	0.192	0.085	0.169	0.047	0.059	0.209	0.034	0.377
CR1	-0.005	0.202	0.141	0.190	0.091	0.014	-0.050	0.054
CR2	0.195	0.212	0.183	0.233	0.135	0.161	-0.058	0.086
PSVR	-0.043	-0.025	0.095	0.257	0.066	0.142	-0.254	-0.033
GEFT2	0.071	0.110	0.023	0.229	0.104	0.123	-0.183	-0.001
GEFT3	0.007	0.109	0.088	0.342	0.153	0.093	-0.124	0.008
HPT1	-0.016	0.167	0.159	-0.035	-0.073	0.128	-0.063	0.085
HPT2	-0.026	0.050	0.136	-0.010	0.016	0.044	-0.098	-0.031
VSAT	0.047	-0.147	0.194	0.337	0.112	-0.055	0.057	-0.076
NS1	0.074	-0.035	0.054	0.303	0.175	0.086	-0.188	0.042
NS2	0.073	0.009	-0.129	0.123	0.105	0.152	-0.033	0.068
DR1	-0.013	0.002	0.192	0.460	0.324	0.154	-0.093	0.144
DR2	-0.005	0.136	0.115	0.357	0.245	0.228	-0.123	0.075
LCIP	0.223	-0.060	-0.140	0.157	0.074	0.327	0.016	0.150
LCIN	-0.040	0.123	0.030	0.123	0.099	-0.087	-0.189	-0.012
UNIT1	0.078	0.213	0.385	0.217	0.250	0.174	-0.024	0.059
UNIT2	0.145	0.226	0.297	0.296	0.357	0.193	-0.070	0.055
UNIT3	-0.018	0.172	0.294	0.107	0.213	0.108	-0.005	0.023
UNIT4	0.142	0.300	0.342	0.328	0.261	0.175	0.078	0.052
FINAL	0.037	0.353	0.321	0.454	0.507	0.393	0.063	0.061

CORRELATION MATRIX FOR MALES

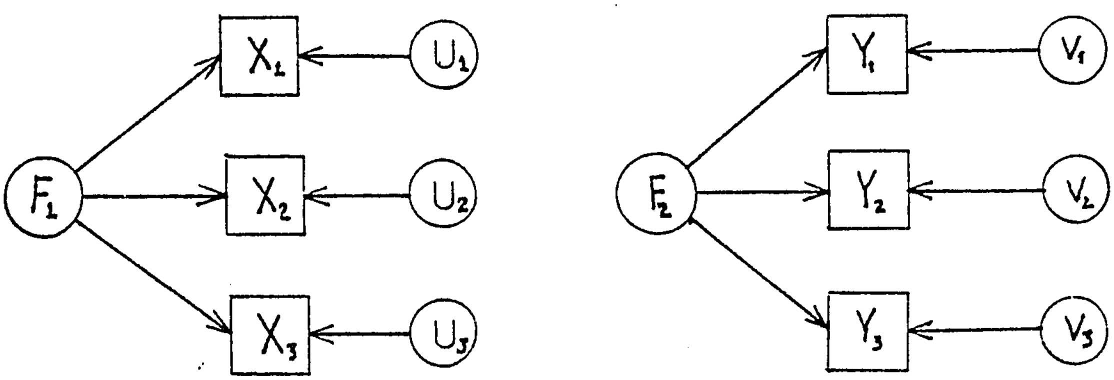
VARIATE	PUMP	PUMN	ROMA	ROPS	AIKP	AIKN	CLMP	CLMN
HSPC	0.294	0.167	0.249	0.132	0.306	0.258	0.354	0.234
HSCA	0.282	0.340	0.296	0.273	0.208	0.184	0.224	0.264
HSPS	0.210	0.138	0.061	0.284	0.280	0.260	0.118	0.148
QSAT	0.372	0.405	0.222	0.394	0.309	0.317	0.264	0.385
ALG	0.363	0.286	0.321	0.360	0.358	0.352	0.280	0.401
TRIG	0.244	0.260	0.371	0.236	0.429	0.463	0.400	0.451
SMDP	0.036	-0.059	-0.075	0.004	-0.132	-0.149	-0.167	-0.105
SMDN	0.224	0.305	0.187	-0.012	0.066	0.063	0.105	0.093
PUMP	1.000	0.804	0.390	0.481	0.603	0.644	0.641	0.619
PUMN	0.804	1.000	0.395	0.450	0.502	0.581	0.545	0.566
ROMA	0.390	0.395	1.000	0.371	0.386	0.377	0.440	0.441
ROPS	0.481	0.450	0.371	1.000	0.168	0.226	0.186	0.256
AIKP	0.603	0.502	0.386	0.168	1.000	0.863	0.794	0.795
AIKN	0.644	0.581	0.377	0.226	0.863	1.000	0.792	0.892
CLMP	0.641	0.545	0.440	0.186	0.794	0.792	1.000	0.805
CLMN	0.619	0.566	0.441	0.256	0.795	0.892	0.805	1.000
EFMP	0.638	0.595	0.241	0.164	0.710	0.644	0.651	0.570
EFMN	0.518	0.614	0.178	0.154	0.669	0.645	0.551	0.593
CR1	0.081	0.200	-0.074	0.158	0.029	0.040	0.083	0.098
CR2	0.212	0.245	0.001	0.229	0.148	0.135	0.185	0.167
PSVE	0.023	0.142	0.097	0.076	0.082	0.139	0.146	0.181
GEFT2	0.095	0.123	0.140	0.119	-0.140	-0.025	0.133	0.021
GEFT3	0.058	0.100	0.197	0.240	0.048	0.102	0.161	0.153
HPT1	0.130	0.135	-0.093	0.022	0.022	-0.020	0.125	-0.072
HPT2	0.007	-0.042	-0.110	-0.035	-0.037	-0.033	0.040	-0.081
VSAT	-0.036	-0.087	-0.070	0.023	-0.086	-0.071	-0.157	-0.209
NS1	0.119	0.280	0.020	-0.034	0.086	0.122	0.077	0.097
NS2	-0.109	0.022	-0.049	-0.141	-0.070	-0.118	0.059	-0.071
DP1	0.189	0.243	0.142	0.028	0.103	0.118	0.086	0.051
DP2	0.282	0.348	0.148	0.167	0.194	0.189	0.230	0.152
LCIP	0.227	0.294	0.063	0.015	0.360	0.330	0.391	0.316
LCIN	-0.134	0.048	0.104	0.013	-0.075	-0.105	0.056	0.081
UNIT1	0.296	0.233	0.254	0.348	0.121	0.181	0.197	0.219
UNIT2	0.389	0.314	0.252	0.496	0.187	0.211	0.150	0.237
UNIT3	0.277	0.177	0.063	0.334	0.259	0.331	0.210	0.298
UNIT4	0.382	0.280	0.048	0.459	0.206	0.297	0.158	0.299
FINAL	0.480	0.433	0.203	0.466	0.370	0.413	0.220	0.423

CORRELATION MATRIX FOR MALES

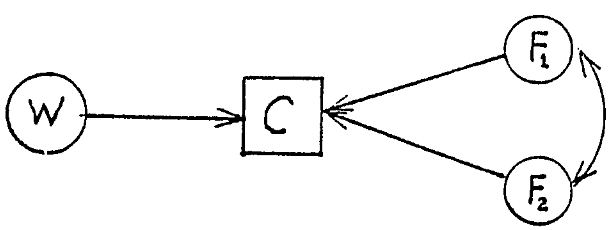
VARIATE	EFMP	EFMN	CR1	CR2	PSVR	GEFT2	GEFT3	HPT1
HSPC	0.404	0.192	-0.005	0.195	-0.043	0.071	0.007	-0.016
HSCA	0.185	0.085	0.202	0.212	-0.025	0.110	0.109	0.167
HSPS	0.231	0.169	0.141	0.183	0.095	0.023	0.088	0.159
QSAT	0.171	0.047	0.190	0.233	0.257	0.229	0.342	-0.035
ALG	0.252	0.059	0.091	0.135	0.066	0.104	0.153	-0.073
TRIG	0.382	0.209	0.014	0.161	0.142	0.123	0.093	0.128
SMDP	0.073	0.034	-0.050	-0.058	-0.254	-0.183	-0.124	-0.063
SMDN	0.374	0.377	0.054	0.086	-0.033	-0.001	0.008	0.085
PUMP	0.638	0.518	0.081	0.212	0.023	0.095	0.058	0.130
PUMN	0.595	0.614	0.200	0.245	0.142	0.123	0.100	0.135
RQMA	0.241	0.178	-0.074	0.001	0.097	0.140	0.197	-0.093
ROPS	0.164	0.154	0.158	0.229	0.076	0.119	0.240	0.022
AIKP	0.710	0.669	0.029	0.148	0.082	-0.140	0.048	0.022
AIKN	0.644	0.645	0.040	0.135	0.139	-0.025	0.102	-0.020
CLMP	0.651	0.551	0.083	0.185	0.146	0.133	0.161	0.125
CLMN	0.570	0.593	0.098	0.167	0.181	0.021	0.153	-0.072
EFMP	1.000	0.811	0.085	0.230	-0.077	0.019	-0.004	0.145
EFMN	0.811	1.000	0.122	0.093	-0.082	-0.113	-0.058	0.128
CR1	0.085	0.122	1.000	0.767	0.186	0.403	0.293	0.334
CR2	0.230	0.093	0.767	1.000	0.153	0.469	0.396	0.402
PSVR	-0.077	-0.082	0.186	0.153	1.000	0.399	0.346	0.113
GEFT2	0.019	-0.113	0.403	0.469	0.399	1.000	0.595	0.336
GEFT3	-0.004	-0.058	0.293	0.396	0.346	0.595	1.000	0.266
HPT1	0.145	0.128	0.334	0.402	0.113	0.336	0.266	1.000
HPT2	0.049	-0.007	0.204	0.287	0.028	0.332	0.282	0.714
VSAT	-0.101	-0.252	-0.034	0.029	0.010	0.079	0.131	-0.026
NS1	0.070	0.130	-0.039	-0.075	0.090	-0.106	0.052	-0.090
NS2	0.019	-0.101	0.200	0.155	0.019	0.194	0.231	0.089
DR1	0.084	-0.096	0.195	0.124	0.250	0.243	0.223	0.001
DR2	0.176	0.114	0.223	0.125	0.197	0.231	0.157	0.171
LCIP	0.379	0.272	0.267	0.340	0.213	0.077	-0.165	0.060
LCIN	-0.126	-0.003	0.332	0.193	0.217	0.253	0.141	0.172
UNIT1	0.228	0.230	0.105	0.074	-0.163	0.019	0.099	0.028
UNIT2	0.173	0.189	0.094	0.170	-0.073	0.110	0.132	0.023
UNIT3	0.199	0.286	0.163	0.184	-0.040	0.020	0.127	0.094
UNIT4	0.241	0.267	0.082	0.149	-0.098	-0.017	0.118	0.098
FINAL	0.351	0.307	0.099	0.201	-0.061	0.008	0.098	-0.040

Here X_1, X_2, X_3, Y_1, Y_2, Y_3, C are measured variables. The X_i are indicators of a latent variable or factor F_1; the Y_i are indicators of a factor F_2. The U_i and V_i are disturbances terms for the X_i and Y_i respectively, and W is the disturbance term of the measured variable C. We can divide this model into a measurement model and structural model as follows:

measurement model



structural model



This is an example of an oblique factor model since the factors F_1 and F_2 are correlated.

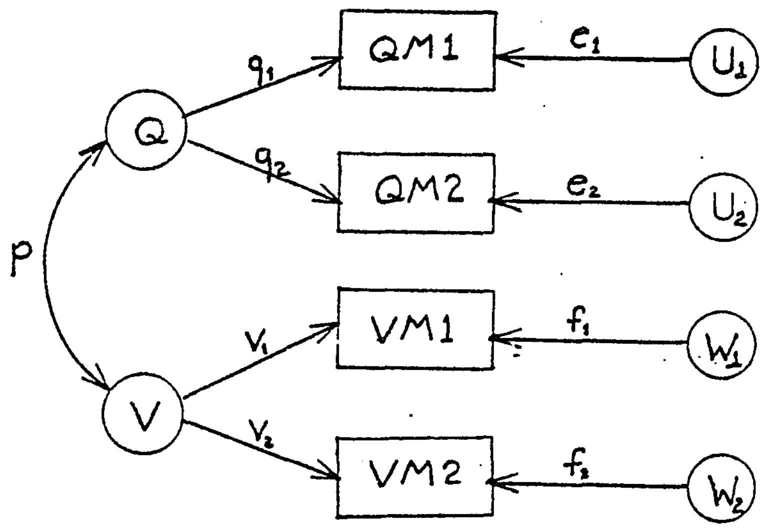
Orthogonal Factor Models vs. Oblique Factor Models

Our primary concern will be with standardized orthogonal factor models, that is, latent variable models for which all the factors are mutually uncorrelated with mean zero and unit variance. Such a model affords especially unambiguous interpretations of the sources of correlations among the measured variables. One sometimes finds the statement made that orthogonal factor models are not as reasonable as oblique models (e.g. Jöreskog & Sörbom, p. 12, 1979). But factors are hypothesized unmeasured causes of the measured variables, and as such they represent the modeler's attempts to explain the correlations between a large number of measured variables in a simpler, more parsimonious manner. Since these constructs are devised as an aid to understanding the underlying structure of the correlations between the measured variables, it appears that the modeler's efforts should be guided by the desire of accounting for the correlations in the most unambiguous manner possible.

An analogy might be drawn from the situation encountered when we try to describe a finite-dimensional real vector space endowed with an inner product. Given a set of vectors, we would like to describe their linear span as economically and as clearly as possible. This leads to the notion of a set of basis vectors. Each of the original vectors can be written as a linear combination of the basis vectors, and no smaller set of vectors will have this same property as the basis vectors. Sets of basis vectors are not unique by any means, so it is desirable to seek a set of basis vectors which has particularly nice properties to aid in analysis. One nice property is that of orthogonality: any two different basis vectors must have a zero inner product. Another nice property is that of normality: each basis vector's inner product with itself is one. Standardized orthogonal factor models meet the same goals, with covariance playing the role of inner product, and the factors providing an "orthonormal basis" in the sense that they are orthogonal (mutually uncorrelated) and normal (with unit variance).

Let us discuss the advantages of orthogonal models over oblique models with an example. Measurements of quantitative and verbal ability are usually positively correlated. If we consider these measurements as indicators of some latent unmeasured constructs of quantitative and verbal ability then it may seem that it is "realistic" to assume that those latent variables are correlated also. However, is it any less "realistic" to assume that there are two uncorrelated constructs and that all the measurements involved have loaded onto both of them? Let us make the distinction a little more precise through the use of path diagrams.

Suppose we have two measures of quantitative ability and two measures of verbal ability. An oblique model might look like:



where Q represents latent quantitative ability

V represents latent verbal ability

QM1, QM2 the two measures of quantitative ability

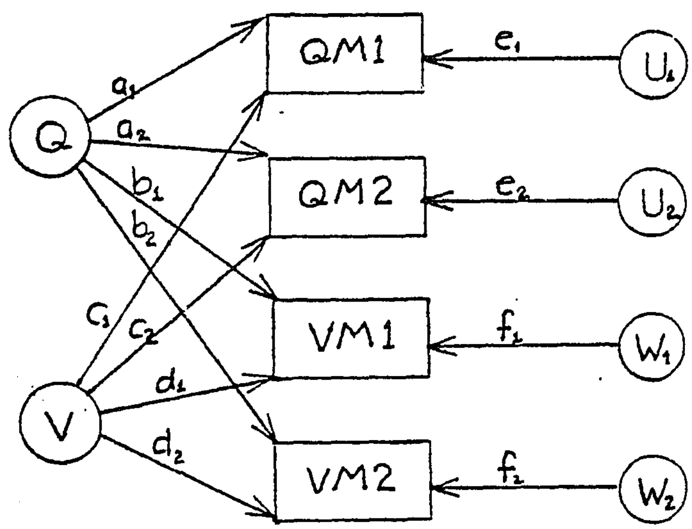
VM1, VM2 the two measures of verbal ability

U_1, U_2, W_1, W_2 are disturbance terms.

Then the correlation between QM1 and VM2 by path analysis is q_1pv_2. Similarly, the correlation between any verbal measure and any quantitative measure involves p, the correlation between the factors Q and V.

One question which comes to mind is: is there an underlying factor structure that explains the correlation between Q and V? Certainly we could explore layers and layers of underlying factor structures ad infinitum in this way. And this question involves the correlations between two variables neither of which can be measured directly!

An alternative model with orthogonal factors would look like:



This model would state that QM1 and VM2 are correlated because they both load on the two factors Q and V. That correlation by path analysis is:

$$a_1 b_2 + c_1 d_2$$

Furthermore we can attach some meaning to each <u>term</u> in this expression. The term a_1b_2 represents the part of the correlation due to the shared cause Q and the term c_1d_2 the part of the correlation due to the shared cause V.

A primary goal of causal modeling in educational studies is a coherent, parsimonious explanation in meaningful terms of the observed correlations between measured variables. If we are utilizing latent unmeasured variables in this explanation there seems to be no pressing reason to insist that oblique factor models are more justifiable than orthogonal factor models. Indeed, perhaps the stronger case can be made for orthogonal factor models, due to the unambiguous attributions of variance and covariance to each factor they provide.

<u>Models to be Developed in this Study</u>

Because of their parsimony and simplicity we chose to concentrate on developing standardized orthogonal factor models. The next chapter is devoted to a discussion of parameter estimation and confirmatory analysis of such models. In particular, a case is made for the use of Lohnes' Factorial Modeling in this regard. This method will be discussed in detail.

Concluding Remarks

Causal modeling in educational research represents a step toward better understanding the complex interactions among the many variables one must contend with in educational environments. As with all research, causal modeling is an iterative process. Different models are devised and compared, and then new models revised from the old ones take their place to be discussed, criticized, and revised yet again. The terminology of structural equations provides a language with which we can better carry on this process of discussion and revision of models. It appears likely that causal modeling deserves and will maintain a prominent position as a tool for multivariate observational studies in general, and particularly in educational research for quite some time to come.

CHAPTER IV

STANDARDIZED ORTHOGONAL FACTOR MODELS AND FACTORIAL MODELING

In this chapter, we discuss the particular type of covariance structural models which we developed in this study: standardized orthogonal factor models. Several methods of parameter estimation are considered, and we make a case for the particular method used in this study-- Factorial Modeling. The use of Factorial Modeling as a confirmatory tool for covariance structural models is also discussed.

Let us review the general context for a standardized orthogonal factor model:

Suppose we have measured p random variables whose correlations we believe can be explained by n underlying orthogonal (uncorrelated) latent (unmeasured) variables. We desire to estimate each latent variable's contribution to explaining the observed variances and covariances of the measured variables. Following Lohnes' (1979) practice we will refer to latent variables as <u>factors</u> and to measured variables as <u>variates</u>. We make the assumption that all variables (measured and unmeasured) are endowed with a standardized metric (mean zero and unit variance). Hence the covariance between any two variables is the same as their correlation. Any variance in a variate not explained by the n common factors is assumed due to a unique factor which includes any errors in measurement. These p unique factors are assumed uncorrelated with the common factors and with each other. We refer to these unique factors as <u>disturbance terms</u>.

Our goal, then, is to estimate the parameters of the following model, which is a standardized orthogonal factor model with n factors and p variates.

Model

Let $X_1, X_2, \ldots, X_p$ denote the p variates;

$F_1, F_2, \ldots, F_n$ denote the n factors;

$U_1, U_2, \ldots, U_p$ denote the p disturbance terms.

$\mathrm{Var}(X_i) = 1 \qquad (i = 1,2,\ldots,p)$

$\mathrm{Var}(F_k) = 1 \qquad (k = 1,2,\ldots,n)$

$\mathrm{Cov}(F_k, F_m) = 0 \qquad (k \neq m;\ k, m = 1,2,\ldots,n)$

$\mathrm{Cov}(U_i, U_j) = 0 \qquad (i \neq j;\ i, j = 1,2,\ldots,p)$

$\mathrm{Cov}(F_k, U_i) = 0 \qquad (k = 1,2,\ldots,n;\ i = 1,2,\ldots,p)$

The p structural equations are:

$$X_1 = s_{11}F_1 + s_{12}F_2 + s_{13}F_3 + \ldots + s_{1n}F_n + d_1U_1$$

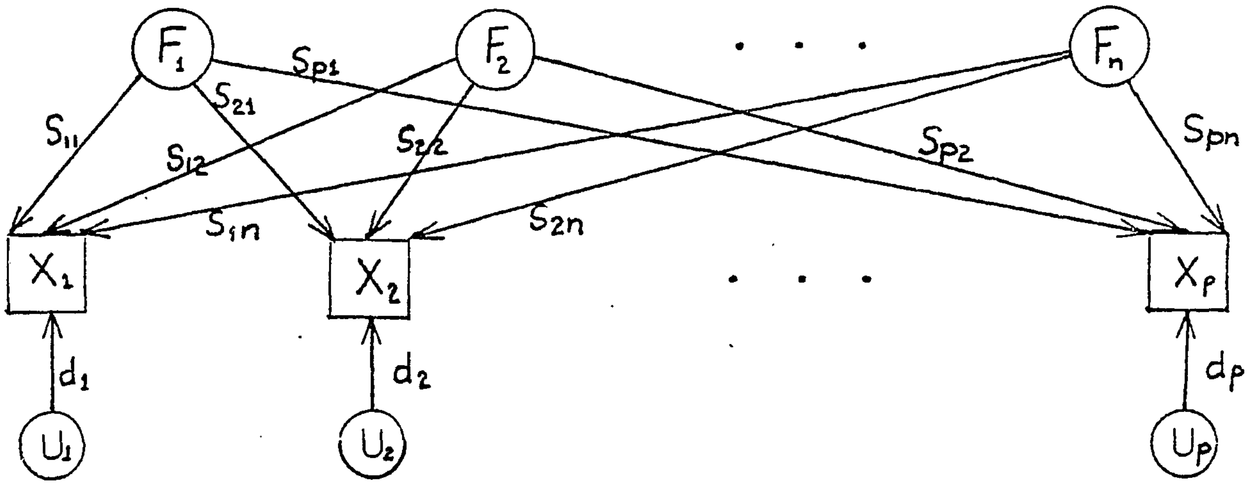
$$X_2 = s_{21}F_2 + s_{22}F_2 + s_{23}F_3 + \ldots + s_{2n}F_n + d_2U_2$$

$$X_3 = s_{31}F_3 + s_{32}F_2 + s_{33}F_3 + \ldots + s_{3n}F_n + d_3U_3$$

$$\vdots$$

$$X_p = s_{p1}F_3 + s_{p2}F_2 + s_{p3}F_3 + \ldots + s_{pn}F_n + d_pU_p$$

In terms of a path diagram our model is as follows:



where the path coefficient on the arrow from F_k to X_i is s_{ik}. Path analysis provides us with the following interpretations:

$s_{ik} = Cov(X_i, F_k)$ = the correlation of X_i and F_k

(s_{ik} is called the <u>loading</u> of X_i on F_k).

$s_{ik}s_{jk}$ = contribution of factor F_k to explaining the correlation between variates X_i and X_j.

d_j^2 = part of variance of X_j unexplained by model

(d_j^2 is sometimes called the <u>unique</u> variance of X_j).

And we define:

$$h_j^2 = \sum_{i=1}^{n} s_{ij}^2 = \text{part of variance of } X_j \text{ explained by model}$$

(h_j^2 is called the <u>communality</u> of X_j).

Note that

$$1 = \mathrm{Var}(X_i) = h_i^2 + d_i^2$$

$$= s_{i1}^2 + s_{i2}^2 + \ldots + s_{in}^2 + d_i^2.$$

and

$$\mathrm{Cov}(X_i, X_j) = \sum_{k=1}^{n} s_{ik} s_{jk}$$

We assume disturbance terms are positively correlated with their corresponding variates. Thus $d_i \geq 0$ for $i = 1,2,\ldots,p$.

<u>Estimation of Model Parameters</u>

The model described above can be described quite simply if we employ the use of matrix algebra notation. Let $\tilde{X}$ denote the column vector (p-dimensional) of the response variates X_1, $X_2,\ldots,$ X_p. That is,

$$\tilde{X}' = (X_1, X_2, \ldots, X_p),$$

where a prime (') denotes a transpose of either a vector or matrix. Similarly let $\tilde{F}$ denote the n-dimensional vector of factors:

$$\tilde{F}' = (F_1, F_2, \ldots, F_n),$$

and let $\tilde{U}$ denote the p-dimensional vector of disturbance terms:

$$\tilde{U}' = (U_1, U_2, \ldots, U_p)$$

If we denote by S the (p x n) <u>loading</u> matrix, i.e., S =

$$\begin{pmatrix} s_{11} & s_{12} & \cdots & s_{1n} \\ s_{21} & s_{22} & \cdots & s_{2n} \\ & \vdots & & \\ s_{p1} & s_{p2} & \cdots & s_{pn} \end{pmatrix}$$

and by D the p x p diagonal matrix with d_i in the ith diagonal entry

$$\begin{pmatrix} d_1 & 0 & \cdots & & 0 \\ 0 & d_2 & 0 & \cdots & 0 \\ 0 & 0 & \cdot & & 0 \\ \vdots & & & \ddots & \vdots \\ 0 & \cdots & & 0 & d_p \end{pmatrix}$$

then we may display the entire set of structural equations as

$$\tilde{X} = S\tilde{F} + D\tilde{U}$$

The standardization assumptions give us the following decomposition of P, the correlation matrix of the variates:

$$P = SS' + DD'$$

where S', D' denote the transpose matrices of S, D respectively. If R denotes a sample correlation matrix and S denotes an estimate of the loading matrix, then we can obtain an estimate of D by letting D be the (p x p) diagonal matrix with the ith diagonal entry equal to the positive square root of the ith diagonal entry of R - SS'. We then need to concern ourselves with how to estimate the loading matrix S. The expected value of F, given X, can be written as

$$E(\tilde{F}|\tilde{X}) = S'P^{-1}\tilde{X}$$

This implies that if we want to estimate factor "scores" by functions of the variates, then linear functions would be most reasonable. That is, each factor is a linear combination of the variates:

$$F_k = b_{k1}X_1 + b_{k2}X_2 + \ldots + b_{kp}X_p \quad (k = 1,2,\ldots,n)$$

or in linear algebraic notation with $\tilde{b}_k' = (b_{k1}, b_{k2},\ldots, b_{kp})$ we have

$$F_k = \tilde{b}_k'\tilde{X}$$

These scoring coefficient vectors $\tilde{b}_k$ must be such that the factors F_k have unit variance and are mutually orthogonal.

With these operational definitions of the factors, the estimates of the structural coefficients can be computed simply as

$$s_{ik} = \mathrm{Cov}(X_i, F_k)$$

One could argue that the factors here are no longer latent variables since they are written as linear combinations of measured variables. However, these factor "scores" are a means to the end goal of estimating the structural parameters of the model. For our purposes they serve as an intermediary computational tool and in the causal modeling setting we need not attach any primary importance to the coefficients b_{ki}. What is important is that these coefficients define linear combinations of the variables that have unit variance and are mutually orthogonal. On the other hand, since our model proposes to explain the underlying structure of the correlations among the variables $X_1, X_2, \ldots, X_p$ in terms of factors that represent our ideas of what latent variables account for those correlations, we should choose "definitions" of the factors that reflect more than just the standardization assumptions of our model. We next discuss some possible strategies for estimating the parameters of the model using operational definitions of the factors.

Principal Components

One method of operationally defining the factors $F_1, F_2, \ldots, F_n$ would be through the use of principal components. That is, we could define F_1 as the first principal component of the variates $X_1, X_2, \ldots, X_p$ (then standardizing by dividing by the square root of the variance), F_2 as the second principal component, F_3 as the third principal component, and so on. This would certainly provide us with mutually orthogonal factors, but we would find that the resulting estimates of structural parameters would provide "over" estimates of the correlations among the variates X_1, $X_2, \ldots, X_p$. This is not surprising, since principal components are defined to maximize the communalities of the variates and as a result will not necessarily fit the sample correlations.

Another problem with using principal components is that these linear combinations which serve as factor definitions are determined completely by the sample correlation matrix and there is no chance for the causal modeler to impose a priori theoretical limitations on the "nature" of these factors. No specific interpretations could be made according to distinctions between factors since they simply represent linear composities which are maximally correlated with the variates. Thus the technique of principal components seems to be better suited to finding the dimensions of common variance between the variates than to obtaining good structural parameter estimates.

Traditional Factor Analysis

The goal of most uses of traditional factor analysis has been to measure the factors with secondary interest in the estimates of structural parameters. As with the technique of principal components, one obtains operational definitions of the factors as linear combinations of the variates. These definitions provide us with factors that have unit variance and are mutually orthogonal. However, unlike principal components, these definitions are made to provide structural parameters which estimate the correlations among variates as closely as possible. There are some uses of factor analysis which provide for oblique (correlated) factors, but these would be inappropriate for our models.

The only modeling constraint one imposes when using factor analysis is in determining n, the number of factors. Past uses of the technique seem to have focused attention on the scoring coefficients for the factors, usually in some attempt to "discover" what the factors are. In this regard one should note that any solution for parameter estimates provided by factor analysis is not unique. Indeed, let S be the (p x n) loading matrix provided by factor analysis and let E denote a diagonal error matrix. Then the (p x p) correlation matrix P could be written as

$$P = SS' + E.$$

Now, let A be any (n x n) orthogonal matrix. (By definition AA' = A'A = I_n, the n x n identity matrix). If we let T = SA, then we have

$$TT' = (SA)(SA)' = (SA)(A'S') = S(AA')S' = SI_nS' = SS'$$

Thus P = TT' + E shows that T provides us with just as "good" of a loading matrix as S. T is considered to be an orthogonal factor rotation of the original factors represented by the structural matrix S.

Traditional factor analysis appears to be better suited for exploratory data analysis than as a causal modeling technique. It could provide us information as to the number of factors which might be required when we are building the model but other techniques would be more appropriate for doing a confirmatory analysis of the model.

Canonical Correlation Analysis

One could attempt to use canonical correlates as factor definitions. This would require designating some set of criterion variates and then computing a set of canonical correlates of this set with the set of remaining variates. The objections to using this technique would be similar to those raised about principal components. It suffices to say that canonical correlation analysis might be appropriate in the exploratory stage of research toward building a model. However, since it leaves little room for the modeler to impose some theoretical restrictions on the nature of factors, it would not be appropriate as a confirmatory tool or for fitting the data.

Maximum Likelihood Factor Analysis

Jöreskog and Sörbom's LISREL is a complex and expensive program for fitting and testing latent variable structural models to sample data. It is appropriate for fitting both the measurement and structural components of the model and the variables may be standardized or not, while the factors can be either oblique or orthogonal. These procedures are being constantly revised and upgraded. Descriptions of the latest version and examples of its use can be found in the LISREL VI Manual (Jöreskog & Sörbom, 1983).

The biggest advantage of LISREL is that by employing maximum likelihood factor analysis one can obtain an overall chi-squared goodness-of-fit test for the model. Unfortunately, the availability of LISREL, perhaps due to its cost, varies widely and many researchers do not have access to it. The particular type of model we are concerned with in this study is a standardized orthogonal factor model. While LISREL could be used to fit and test such a model there exists a much simpler and less expensive technique, namely Factorial Modeling.

Factorial Modeling

Factorial Modeling (FaM) is the name Langley has given to the method Lohnes developed for fitting a causal model with hypothesized latent orthogonal causes to data which have been reduced to a correlation matrix. The name invites a comparison with factor analysis, and the models fitted by each are similar in structure. However, factor analysis requires only that the number of factors in the model be determined beforehand. Factorial Modeling requires the following:

1) a numbering of the factors and the specification of each factor by two or more variates.

2) the identification of a key criterion variate to which the factors will be oriented.

3) an ordering of factors for extraction from the correlation matrix.

To understand the technique of Factorial Modeling, it is best to consider the more general class of factor extraction techniques of which it is a member.

A General Factor Extraction Technique

The mathematics behind the method uses neither the calculus of a least squares approach nor the maximum likelihood factor analysis of a LISREL approach. Rather it is based on some fairly simple linear algebraic techniques for extracting arbitrary orthogonal factors from a correlation matrix. This work was pioneered by Guttman in the 1940's and 1950's (Guttman, 1948, 1944, 1952; Thurstone, 1945). Factorial Modeling represents a special application of these techniques. Overall (1962) provided a proof that the factors extracted by such a technique are uncorrelated. (see also Cooley & Lohnes, 1971).

The general method of extraction can be described as follows:

Suppose we have p standardized variables X_1, $X_2, \ldots,$ X_p. Then their correlation matrix is the same as their covariance matrix. If a factor f_1 is "defined' as some linear combination of these variables, i.e.

$$f_1 = a_1X_1 + a_2X_2 + \ldots + a_pX_p,$$

then we want to standardize this factor and extract it from the correlation matrix.

In linear algebraic terms, if $\tilde{X}' = (X_1, X_2, \ldots, X_p)$ represents the vector of response variates, and R_1 represents the correlation matrix of the X_i's, i.e., R_1 =

$$\begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1p} \\ r_{21} & r_{22} & \cdots & r_{2p} \\ & & \cdot & \\ & & \cdot & \\ & & \cdot & \\ r_{p1} & r_{p2} & \cdots & r_{pp} \end{pmatrix}$$

where r_{ij} = correlation between X_i and X_j, then we can write

$$f_1 = \tilde{a}'\tilde{X}$$

where $\tilde{a}' = (a_1, a_2, \ldots, a_p)$. The variance of f_1 can be written as

$$\mathrm{Var}(f_1) = \tilde{a}'R_1\tilde{a}.$$

Thus

$$F_1 = f_1 / \sqrt{\tilde{a}'R_1\tilde{a}}$$

is a standardized factor (mean zero and unit variance). We extract F_1 from the correlation matrix by partialling out its influence from each of the p variables, and then recomputing their covariances. This new variance-covariance matrix is referred to as the residual matrix.

Another way of looking at this extraction process is to simply note that we are defining p new variables:

$$\hat{X}_1 = X_1 - \mathrm{Cov}(X_1,F_1)F_1$$
$$\hat{X}_2 = X_2 - \mathrm{Cov}(X_2,F_1)F_1$$
$$\vdots$$
$$\hat{X}_p = X_p - \mathrm{Cov}(X_p,F_1)F_1$$

These new variables are all uncorrelated with F_1, since for $i = 1,2,\ldots,p$ we have

$$\begin{aligned}\mathrm{Cov}(\hat{X}_i,F_1) &= \mathrm{Cov}(X_i - \mathrm{Cov}(X_i,F_1)F_1,\ F_1)\\ &= \mathrm{Cov}(X_i,F_1) - \mathrm{Cov}(X_i,F_1)\mathrm{Cov}(F_1,F_1)\\ &= \mathrm{Cov}(X_i,F_1) - \mathrm{Cov}(X_i,F_1)\\ &= 0.\end{aligned}$$

If we compute the covariance matrix of these new variables and denote it by R_2, then R_2 represents the residual correlation matrix of the original variables after the factor F_1 has been extracted. In matrix terms:

$$R_2 = R_1 - \tilde{s}_1\tilde{s}_1'$$

where $\tilde{s}_1' = (\mathrm{Cov}(X_1,F_1),\ \mathrm{Cov}(X_2,F_1),\ldots,\ \mathrm{Cov}(X_p,F_1))$.

Now, since the variables $\hat{X}_1$, $\hat{X}_2$,..., $\hat{X}_p$ are each uncorrelated with F_1, any linear combination of these variables, such as

$$f_2 = b_1\hat{X}_1 + b_2\hat{X}_2 + \ . \ . \ . + b_p\hat{X}_p$$

is uncorrelated with F_1 also. If we denote the coefficient vector by $\tilde{b}' = (b_1, b_2, \ldots, b_p)$, then the factor

$$F_2 = f_2 / \sqrt{Var(f_2)} \quad = f_2 / \sqrt{\tilde{b}'R_2\tilde{b}}$$

will be standardized and orthogonal to F_1. We can then define p new variables by setting

$$\hat{\hat{X}}_i = \hat{X}_i - Cov(\hat{X}_i, F_2)F_2$$

$$= X_i - Cov(X_i, F_1)F_1 - Cov(X_i, F_2)F_2$$

for $i = 1,2,\ldots,p$. It is easy to check that for $i = 1,2,\ldots,p$

$$0 = Cov(\hat{\hat{X}}_i, F_1) = Cov(\hat{\hat{X}}_i, F_2)$$

We can now compute the vector of structural coefficients from the second factor as:

$$\tilde{s}_2' = (Cov(X_1, F_2), Cov(X_2, F_2), \ldots, Cov(X_p, F_2))$$

The variance-covariance matrix of these new variables, which we may think of as the original correlation matrix with the factors F_1 and F_2 extracted is

$$R_3 = R_2 - \tilde{s}_2\tilde{s}_2'$$

We can continue this process until any desired number of factors is extracted. Note that if one uses these factors to estimate structural parameters, then those parameters are given by the vectors $\tilde{s}_k$. In other words the loading matrix would be

$$S = (\tilde{s}_1\ \tilde{s}_2\ \tilde{s}_3\ .\ .\ .\ \tilde{s}_n).$$

The Use of Specifying Variates and a Key Criterion in FaM

Factorial Modeling is distinguished as a particular case of the general orthogonal factor extraction technique discussed above. This distinction involves the requirements FaM makes on the factors that may be extracted.

Suppose we have measured variables X_1, $X_2, \ldots,$ X_p as before and that we are considering an orthogonal factor model with n factors F_1, $F_2, \ldots,$ F_n. FaM requires:

1) a set of specifying variates for each factor. Each factor must have associated to it a set of two or more variates. These sets of variates must be mutually exclusive. That is, no measured variable can act as a specifying variate for more than one factor. However,

these sets do not form a partition of the variates $X_1, X_2, \ldots, X_p$ since at least one variate must not be a specifying variate for any of the factors.

2) a <u>key criterion variate</u> for orienting the factors. As could be seen in the description of the general extraction technique, a factor is "defined" at any particular step by a linear combination of variables representing the original variables $X_1, X_2, \ldots, X_p$ after all the factors extracted in previous steps have been partialled out. In FaM, the specifying variates determine <u>which</u> of the variables will be involved in this linear combination. A key criterion will determine the <u>coefficients</u> of those variables in the linear combination. The key criterion variate is chosen from amongst the measured variables not used as specifying variates. The coefficient of each variable is its correlation with this key criterion.

For example, suppose $R_k = (r_{ij})$ is the residual correlation matrix of the variables $X_1, X_2, \ldots, X_p$ <u>after</u> factors $F_1, F_2, \ldots, F_{k-1}$ have been extracted. In other words, R_k represents the variance-covariance matrix for variables $Y_1, Y_2, \ldots, Y_p$ where $Cov(Y_i, F_j) = 0$ for $i=1,2,\ldots,p$; $j=1,2,\ldots, k-1$. If the specifying variates for factor F_k are $X_1, X_2, \ldots, X_q$ and the key criterion is X_p, then we would let

$$f_k = r_{1p}Y_1 + r_{2p}Y_2 + \ldots + r_{qp}Y_q$$

and

$$F_k = f_k / \sqrt{Var(f_k)}$$

would be standardized.

As before, the structural coefficients for the path from F_k to X_i would be

$$s_{ik} = \mathrm{Cov}(X_i, F_k)$$

for i = 1,2,...,p and the residual correlation matrix for the next step would be

$$R_{k+1} = R_k - \tilde{s}_k \tilde{s}_k'$$

where $\tilde{s}_k$ is the column vector of those structural coefficients. This matrix would represent the correlation matrix after factors F_1, F_2,... F_k had been extracted.

3) an order for extraction of the factors. Because of the use of weights (the coefficients of the specifying variates in each step) based on a key criterion, the structural coefficients estimated by FaM are not independent of the order of extraction. Hence some ordering must be decided on beforehand. This may be viewed as the price paid for using the simpler linear algebraic extraction process in lieu of least squares or maximum likelihood techniques.

This order carries with it the following interpretation of the structural parameters: s_{ik} is the effect (measured in standard deviations increase) on the variate X_i resulting from one standard deviation increase in the factor F_k, <u>after</u> factors F_1, F_2,..., F_{k-1} have been controlled.

Summary of the FaM Algorithm

We are now in a position to summarize the previous discussion by outlining the step-by-step algorithm for Factorial Modeling.

Let $X_1, X_2, \ldots, X_p$ be the standardized measured variables (variates) for which we desire a standardized orthogonal factor model with factors $F_1, F_2, \ldots, F_n$ and uncorrelated disturbance terms. We will denote the variate response vector by

$$\underset{\sim}{X}' = (X_1, X_2, \ldots, X_p)$$

and let R denote the sample correlation matrix for $X_1, X_2, \ldots, X_p$, that is, R =

$$\begin{pmatrix} r_{11} & r_{12} & r_{13} & \ldots & r_{1p} \\ r_{21} & r_{22} & r_{23} & \ldots & r_{2p} \\ & & \cdot & & \\ & & \cdot & & \\ & & \cdot & & \\ r_{p1} & r_{p2} & r_{p3} & \ldots & r_{pp} \end{pmatrix}$$

where r_{ij} is the sample correlation between X_i and X_j.

Let $\underset{\sim}{F}' = (F_1, F_2, \ldots, F_n)$ and let I_1 be the (p x p) diagonal matrix with 1's in the diagonal entries corresponding to the specifying variates of the first factor and 0's elsewhere. For example, if the specifying variates for the first factor are X_1, X_3, and X_7, then I_1 is a (p x p) matrix with a "1" in the first, third, and seventh diagonal positions and zeroes in all other entries.

Let $\tilde{r}_1$ denote the column of the correlation matrix $R_1 = R$ which corrresponds to the key criterion variate. That is

$$\tilde{r}_1' = (r_{1c}, r_{2c}, \ldots, r_{pc})$$

where C denotes the key criterion variate. Then

$$\tilde{v}_1 = I_1 \tilde{r}_1$$

denotes the coefficient vector for the first factor before standardization, i.e.

$$f_1 = \tilde{v}_1' \tilde{X}$$

To standardize the factor we must compute the variance of the linear combination of the X_i's represented by v_1:

$$\mathrm{Var}(f_1) = \tilde{v}_1' R_1 \tilde{v}_1$$

If we let

$$\tilde{h}_1 = \tilde{v}_1 \ / \ \sqrt{\tilde{v}_1' R_1 \tilde{v}_1}$$

then h_1 denotes the coefficient vector of the standardized factor. Thus the first factor is defined as

$$F_1 = \tilde{h}_1' \tilde{X}$$

The coefficient of the first factor in the structural equation for X_1 is

$$s_{11} = \mathrm{Cov}(X_1, F_1)$$

The vector of these structural coefficients is

$$\tilde{s}_1' = (s_{11}, s_{21}, \ldots, s_{p1})$$

i.e.,

$$\tilde{s}_1 = R_1\tilde{h}_1$$

To extract the factor from the correlation matrix we compute

$$R_2 = R_1 - \tilde{s}_1\tilde{s}_1'$$

We can now outline the process recursively.

If:

R_k = residual correlation matrix after extraction of (k-1) factors,

$\tilde{r}_k$ = column of R_k corresponding to the key criterion,

I_k = (p x p) diagonal matrix with 1's in entries corresponding to specifying variates for kth factor and 0's elsewhere,

then the unstandardized coefficient vector for the kth factor is

$$\tilde{v}_k = I_k\tilde{r}_k.$$

The standardized factor is determined by the coefficient vector

$$\tilde{h}_k = \tilde{v}_k \;/\; \sqrt{\tilde{v}_k{}' R_k \tilde{v}_k}$$

and the structural coefficients of the kth factor are given by the vector

$$\tilde{s}_k = R_k \tilde{h}_k .$$

The residual correlation matrix after extraction of this kth factor is

$$R_{k+1} = R_k - \tilde{s}_k \tilde{s}_k{}' .$$

After all n factors have been extracted we let

$$S = (\tilde{s}_1 \;\; \tilde{s}_2 \;\; \ldots \;\; \tilde{s}_n)$$

be the (p x n) loading matrix obtained from the n column vectors $\tilde{s}_1$, $\tilde{s}_2$,... , $\tilde{s}_n$, and we let

D = the diagonal matrix with diagonal entries equal to the square roots of the diagonal entries of R_{n+1}.

This gives us all of the parameters of the model

$$\tilde{X} = S\tilde{F} + D\tilde{U}$$

The model's estimate of the correlation matrix is

$$\hat{R} = SS' + DD'$$

and we note that the original correlation matrix can be recovered with

$$R = SS' + R_{n+1}$$

One may express each factor as a linear combination of X_1, $X_2, \ldots, X_p$ also, though these factor "scores" are of secondary importance in terms of our model. That is, each factor may be written in the form

$$F_k = \tilde{b}_k{}'\tilde{X}$$

for $k = 1,2,\ldots,n$, where $\tilde{b}_k$ is the (p x 1) scoring vector of coefficents. These can be expressed recursively if we write

$$\tilde{b}_1 = \tilde{h}_1$$

and

$$\tilde{b}_k = \tilde{h}_k - \tilde{h}_k{}'\tilde{s}_{k-1}\tilde{b}_{k-1} - \tilde{h}_k{}'\tilde{s}_{k-2}\tilde{b}_{k-2} - \ldots - \tilde{h}_k{}'\tilde{s}_1\tilde{b}_1$$

for $k = 2,3,\ldots,n$. Thus the kth factor is operationally defined as a linear combination of the specifying variates for the first k factors.

The communality of the jth variate is given as

$$h_j^2 = \tilde{\hat{s}}_j{}'\tilde{\hat{s}}_j$$

and its disturbance term coefficient is

$$d_j = \sqrt{1 - h_j^2} \ ,$$

or the jth diagonal entry of D, for $j = 1,2,\ldots,p$.

Advantages and Limitations of FaM

Some of the advantages of FaM have been mentioned already. It is simple mathematically, especially compared to LISREL, and FaM estimates the parameters for an orthogonal factor model quite efficiently. It allows the modeler to impose theoretical considerations through the choices of specifying variates and a key criterion variate.

Objections to the use of FaM would almost certainly center on the a priori decisions which must be made before the algorithm is employed: the number of factors, specifying variates for each factor, a key criterion and an order for factor extraction must all be determined in advance of the computation of parameter estimates. However, one must remember that FaM is a confirmatory tool for causal models. Previous research and exploratory statistical work is the ground on which factor models are built. We must have good reasons for our choices of specifying variates and a key criterion.

In educational research, a key criterion variable is often a logical choice to make. For example, in the present study we were interested in the correlations among cognitive and affective variables with mathematics achievement and participation. A logical choice for the key criterion would be that measure which represents a student's most recent mathematics achievement-- the score on the final exam in calculus. Evidence provided by exploratory principal components and factor analyses can help us make a well-founded choice for the number of factors. Specifying variates for each factor may be chosen based on similar exploratory statistical work and content considerations. For example, if we feel that there is a factor representing latent spatial ability, a battery of spatial ability measures would be a likely choice for the set of specifying variates for that factor.

The most troublesome objection would probably be with the order dependence inherent in the FaM algorithm. There seems no way around this problem without altogether abandoning the simpler linear algebra for more complicated procedures. However, the order of extraction need not be arbitrary and can be guided by other considerations. Because at each stage of the extraction process we are dealing with the residual covariances after previous factors have been extracted, the earlier a factor is extracted, the greater is its "opportunity" to explain the correlations. We may want to take advantage of this fact to reflect our ideas of which variables play the greatest role in explaining the correlations. Keeping this order in mind allows us to interpret the structural coefficients of the kth factor as its influence after partialling out the first (k - 1) factors. Indeed, this implies that the contributions of the last factor as evidenced by its structural coefficients are contributions after all other factor influences have been controlled. The order of factors then is perhaps not so objectionable if we make sure to consider it when we interpret the parameter estimates provided by FaM. Put another way, the order of the factors is as much a part of our model as the structural parameters.

Extensions of FaM

Factorial Modeling uses a key criterion variate to determine the coefficients or weightings of the specifying variates defining each factor. There are alternatives to this weighting scheme.

Suppose the factor F_k is specified by the variates X_1, $X_2, \ldots, X_q$. Then in FaM we consider the linear combination

$$f_k = r_{1c}Y_1 + r_{2c}Y_2 + \ldots + r_{qc}Y_q$$

where Y_i = the variable corresponding to X_i after the first (k - 1) factors have been already extracted (so Y_i is orthogonal to factors F_1, $F_2, \ldots, F_{k-1}$) and $r_{ic} = \mathrm{Cov}(Y_i, C)$ is the covariance between Y_i and the criterion variate C.

We define

$$F_k = f_k / \sqrt{\mathrm{Var}(f_k)}$$

In this way, F_k has mean zero (since each X_i has mean zero), unit variance, and is orthogonal to factors $F_1, F_2, \ldots, F_{k-1}$.

Weightings of the specifying variates other than the residual correlations with the criterion variate could have been chosen. That is, if we let

$$g_k = t_1Y_1 + t_2Y_2 + \ldots + t_qY_q$$

and define

$$G_k = g_k / \sqrt{Var(g_k)}$$

then G_k will also have mean zero, unit variance, and be orthogonal to the first (k - 1) factors. What is crucial, then, is how one chooses the coefficients $t_1, t_2, \ldots, t_q$. We list some possible alternatives to the choices made by FaM:

1) unit weightings

We could let $t_1 = t_2 = \ldots = t_q = 1$ at each step of the extraction process. This would remove any dependence on a key criterion, but there would still be an order dependence in the factor extraction process.

2) different key criterion for each factor

We could vary the key criterion used with each factor. These key criteria could be specified individually before the extraction process begins. Another alternative which Lohnes has adapted is the specification of a set of key criteria. At each stage of the extraction process, the criterion variate is chosen which enjoys the largest sum of squares of residual correlations with the specifying variates of the factor currently being extracted. This alternative is attractive if there is more than one variate which might serve well as a key criterion.

3) principal component weightings

Given specifying variates X_1, $X_2, \ldots,$ X_q, we could take the coefficients yielding the first principal component of Y_1, $Y_2, \ldots,$ Y_q. Again, this would remove dependence on a key criterion, yet it may give undue prominence to the early factors in the extraction process.

4) multiple regression/ canonical correlate weightings

Given specifying variates and a key criterion, one could take the regression weights of the variates on the key criterion as the FaM weights. If there are multiple key criteria available, one could use the weights given by the first canonical correlate of the specifying variates with the key criteria.

Both the principal components and multiple regression/ canonical correlate suggestions complicate the mathematics of the original technique since these involve least-squares and/or eigenvector determinations at each stage of the process. The replicability of the estimates for structural parameters in the model may become more sensitive to random variability in sample data when using these maximization techniques. The reader will have to decide if any of these alternative weighting schemes would serve any particular research purposes better than the original FaM weighting technique.

Goodness-of-Fit for Factorial Modeling

Unlike LISREL, there is no statistical goodness-of-fit test developed at present for models fitted by FaM. Lohnes has discussed some possibilities for such a test (Lohnes, 1983). Monte Carlo experiments might indicate which of these represents the best test to use in conjunction with FaM.

One statistic which is particularly appealing on intuitive grounds is the root mean square of the distinct residual correlations. In mathematical notation, we can write this statistic as follows:

$$\mathrm{RMS} = \sqrt{(2/(p(p + 1)))\mathrm{ttr}(r_{ij}^2)}$$

where p is the number of variates, and $\mathrm{ttr}(r_{ij}^2)$ is the sum of the squares of the residual correlations above the main diagonal of the residual correlation matrix. This statistic is attractive since it is completely determined by the squared residual correlations, giving us some measure of how much of the correlations is not explained by our model. Note that if we had a perfect fit for our model, then RMS would equal zero. At present there seems to be no distribution theory developed for this statistic. We would note, however, its similarity to a statistic that Lawley suggested in 1940 (see Morrison, 1976) as a test statistic for a diagonal covariance matrix from a multivariate normal population. This statistic is:

$$\chi^2 = (N - 1 - (2p + 5)/6)\mathrm{ttr}(r_{ij}^2)$$

where N is the number of subjects in the sample, p is the number of variates, and r_{ij} is the ijth entry from the sample correlation matrix. Lawley's statistic is distributed approximately as a chi-squared statistic with $p(p - 1)/2$ degrees of freedom under the assumption of a multivariate normal distribution for the variates involved. This approximation is best when the sample correlations are small. While it appears potentially useful with regards to FaM, we must keep in mind that RMS involves the residual correlation matrix. We do not know what adjustments, if any, could be made to Lawley's statistic so that it would provide a chi-squared goodness-of-fit test for FaM when residual correlations are used. One could try replacing p by $(p - n)$, where n is the number of factors, to account for the correlation matrix's rank being reduced in rank from p to $(p - n)$, due to the factor extraction process.

Lohnes has also suggested that the residual correlation matrix be sent to a principal components analysis (Lohnes, 1979). Such a procedure would indicate the sufficiency of the number of factors proposed by the model, as well as point to possible directions for subsequent revision of the model. Even though there is at present no statistical goodness-of-fit test for Factorial Modeling, we can see that the residual matrix R_{n+1} can still give us some helpful information regarding how well our model fits the data by examining its off-diagonal entries.

Summary

Factorial Modeling is a parameter estimation and model-fitting technique appropriate for special types of causal models: standardized orthogonal factor models. It allows the researcher to impose theoretical restrictions on the factors by requiring specifying variates for each factor and a key criterion variate for orienting the factors. The main objection that could be raised about the technique is that it also requires an ordering of the factors for extraction. Still, it seems much more appropriate for parameter estimation than the techniques of principal components, traditional factor analysis, or canonical correlates. These techniques place the researcher at the mercy of the particular sample correlation matrix at hand with little opportunity to place any sensible restrictions on the factors. On the other hand, by employing the more elementary linear algebraic factor extraction techniques of Guttman, FaM is a much simpler technique to use than the expensive and complex LISREL techniques. If the researcher did desire to make use of principal components, factor analysis or canonical correlates for more than exploratory purposes, the algorithm FaM is based on is flexible enough to incorporate these techniques in the weighting scheme for the specifying variates. We conclude that Factorial Modeling is an alternative well worth considering for fitting standardized orthogonal factor models to sample data and we make use of it in our present study.

CHAPTER V

RESULTS OF THE EXPLORATORY ANALYSIS

In this chapter we provide the results of the analysis using the first subsample of students (N = 134; 62 females and 72 males). We provide descriptive statistics on each of the 37 measures employed in the study. These statistics include the mean and standard deviation of each measure for males and females (Table 7), and the covariances and correlations of each measure with the others, also computed separately for males and females (Table 8). All of these sample statistics were computed by the method of maximum likelihood.

Of particular importance in this study was the result of the test of the null hypothesis:

$$H_0: \quad \Sigma_f = \Sigma_m$$

where Σ_f and Σ_m denote the variance-covariance matrix of the measures for females and males, respectively. The test statistic used in this regard was Box's M statistic, which has a distribution which can be approximated as an F statistic (see Morrison, 1976). The variance-covariance matrices for males and females were found to be significantly different ($p < .0001$). This indicated that separate covariance structural models should be developed for males and females.

Although the assumptions required for a discriminant analysis were not met, we include the results of this procedure in Table 9. This serves two purposes. For the reader who feels that discriminant analysis is robust enough to withstand a violation of the assumption of equal variance-covariance matrices, this information may prove to be that of most interest. It also provides a review of the abbreviations used for the various measures (as described in Tables 1-4 on pages 39-41).

Next, we note what exploratory techniques, such as principal component analysis, canonical correlate analysis, and traditional factor analysis, indicated in terms of developing standardized orthogonal factor models for the measures. Here we were concerned with such things as the appropriate number of factors for the models and determining specifying variates for each factor, in anticipation of performing the confirmatory analysis with Factorial Modeling (FaM).

In Chapter VI we describe our proposed factor models, the results of the parameter estimation and confirmatory analysis with FaM, and the indications for the goodness of fit of our models.

On the following pages, we give the descriptive statistics for the first subsample and the results of the discriminant analysis in Tables 7-9.

Table 7. Means and standard deviations for first subsample

DESCRIPTIVE STATISTICS FOR FIRST SUBSAMPLE

	FEMALES		MALES	
VARIATE	MEAN	ST. DEV.	MEAN	ST. DEV.
QSAT	554.68	62.26	580.83	76.70
VSAT	491.29	69.04	498.47	76.35
HSPC	26.15	5.71	25.83	6.11
HSCA	3.08	3.73	3.86	3.87
HSPS	13.61	5.24	15.72	5.19
RQMA	10.26	14.20	13.06	9.87
RQPS	15.60	24.48	46.11	33.20
ALG	13.74	4.42	15.89	4.06
TRIG	4.35	2.81	5.47	2.60
UNIT1	88.06	12.40	91.26	7.47
UNIT2	63.35	24.15	78.33	15.85
UNIT3	70.58	28.05	82.25	13.58
UNIT4	57.69	30.15	73.72	21.57
FINAL	17.74	8.24	21.26	6.92
GEFT2	6.29	2.25	6.76	1.89
GEFT3	7.89	1.72	8.10	1.35
HPT1	107.60	17.98	111.92	16.88
HPT2	109.34	18.21	113.17	16.18
NS1	3.55	4.47	3.01	4.50
NS2	4.82	4.26	5.15	4.35
DR1	9.94	11.68	9.25	2.99
DR2	10.33	3.09	10.35	3.27
CR1	66.24	11.24	59.82	15.75
CR2	56.05	10.97	53.13	14.56
PSVR	5.97	2.96	7.07	3.18
AIKP	33.19	9.08	34.16	8.32
AIKN	36.02	8.67	37.65	8.37
CLMP	21.38	4.07	22.63	4.39
CLMN	22.38	5.56	23.28	4.90
PUMP	22.80	5.75	25.73	3.71
PUMN	23.56	5.22	25.55	4.70
SMDP	26.95	3.61	25.79	4.06
SMDN	26.49	4.22	25.19	4.08
EFMP	20.05	5.29	21.21	3.39
EFMN	21.35	5.96	22.71	4.30
LCIP	5.17	1.53	5.88	1.58
LCIN	5.14	2.03	5.35	1.68

Table 8. Covariances and correlations for first subsample

VARIATE: QSAT (N = 134; 62 FEMALES AND 72 MALES)

	COVARIANCES		CORRELATIONS	
VARIATE	FEMALES	MALES	FEMALES	MALES
QSAT	3876.51	5882.64	1.000	1.000
VSAT	1277.84	1776.27	0.297	0.303
HSPC	78.35	29.44	0.220	0.063
HSCA	55.43	89.84	0.239	0.303
HSPS	14.71	64.68	0.045	0.163
ROMA	157.18	114.68	0.178	0.152
ROPS	286.08	578.10	0.188	0.227
ALG	125.40	135.93	0.456	0.436
TRIG	50.11	60.58	0.286	0.303
UNIT1	392.12	176.86	0.508	0.309
UNIT2	844.47	603.06	0.562	0.496
UNIT3	720.35	268.26	0.412	0.258
UNIT4	799.98	469.26	0.426	0.284
FINAL	225.56	248.95	0.440	0.469
GEFT2	74.45	-0.64	0.532	-0.004
GEFT3	47.62	-0.36	0.444	-0.003
HPT1	306.40	154.93	0.274	0.120
HPT2	319.38	146.11	0.282	0.118
NS1	79.21	74.02	0.284	0.215
NS2	97.28	65.98	0.366	0.198
DR1	29.84	69.62	0.041	0.304
DR2	103.37	90.16	0.537	0.360
CR1	45.80	87.65	0.065	0.073
CR2	55.42	101.15	0.081	0.091
PSVR	82.09	66.33	0.446	0.272
AIKP	186.60	243.98	0.330	0.383
AIKN	226.17	272.17	0.419	0.424
CLMP	108.51	95.22	0.428	0.253
CLMN	178.09	156.16	0.514	0.415
PUMP	113.06	79.24	0.316	0.278
PUMN	102.70	40.71	0.316	0.113
SMDP	28.16	-60.40	0.125	-0.194
SMDN	57.69	-18.12	0.219	-0.058
EFMP	110.75	107.18	0.337	0.412
EFMN	116.95	90.08	0.315	0.243
LCIP	32.34	-9.55	0.340	-0.079
LCIN	65.82	5.51	0.521	0.043

VARIATE: VSAT (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
QSAT	1277.84	1776.27	0.297	0.303
VSAT	4766.08	5829.61	1.000	1.000
HSPC	-14.86	-94.56	-0.038	-0.203
HSCA	40.70	37.98	0.158	0.129
HSPS	64.21	10.69	0.178	0.027
ROMA	53.86	-13.39	0.055	-0.018
ROPS	120.84	-73.16	0.071	-0.029
ALG	32.75	35.66	0.107	0.115
TRIG	25.19	26.42	0.130	0.133
UNIT1	143.30	-2.51	0.167	-0.004
UNIT2	219.86	20.93	0.132	0.017
UNIT3	66.51	-13.78	0.034	-0.013
UNIT4	-143.96	131.38	-0.069	0.080
FINAL	119.36	50.96	0.210	0.096
GEFT2	13.98	10.47	0.090	0.073
GEFT3	-3.08	14.45	-0.026	0.141
HPT1	1.65	-126.52	0.001	-0.098
HPT2	54.40	6.50	0.043	0.005
NS1	62.03	120.99	0.201	0.352
NS2	94.75	61.90	0.322	0.186
DR1	-67.18	95.00	-0.083	0.416
DR2	50.86	56.33	0.238	0.226
CR1	166.14	-219.58	0.214	-0.183
CR2	-14.42	-136.89	-0.019	-0.123
PSVR	43.59	39.13	0.214	0.161
ATKP	-85.53	-66.26	-0.136	-0.104
ATKN	-102.13	41.92	-0.171	0.066
CLMP	1.06	29.70	0.004	0.089
CLMN	-23.19	88.29	-0.060	0.236
PUMP	-62.29	-15.01	-0.157	-0.053
PUMN	-59.46	-21.44	-0.165	-0.060
SMDP	-12.23	-30.42	-0.049	-0.098
SMDN	0.05	57.46	0.000	0.184
EFMP	-59.41	5.10	-0.163	0.020
EFMN	-82.37	11.71	-0.200	0.036
LCIP	-11.79	-14.53	-0.112	-0.120
LCIN	56.19	-17.77	0.401	-0.139

VARIATE: HSPC (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
OSAT	78.35	29.44	0.220	0.063
VSAT	-14.86	-94.56	-0.038	-0.203
HSPC	32.58	37.39	1.000	1.000
HSCA	6.89	2.17	0.324	0.092
HSPS	2.19	5.47	0.073	0.172
ROMA	4.51	-12.38	0.056	-0.205
ROPS	0.19	13.32	0.001	0.066
ALG	8.33	4.90	0.330	0.197
TRIG	2.61	-0.02	0.163	-0.001
UNIT1	22.26	9.84	0.314	0.215
UNIT2	56.82	13.51	0.412	0.139
UNIT3	64.04	13.10	0.400	0.158
UNIT4	64.11	37.22	0.373	0.282
FINAL	12.65	12.03	0.269	0.284
GEFT2	1.07	1.53	0.084	0.132
GEFT3	-0.18	-0.01	-0.018	-0.001
HPT1	22.67	4.01	0.221	0.039
HPT2	4.61	9.83	0.044	0.099
NS1	1.97	-2.07	0.077	-0.075
NS2	-1.36	-2.04	-0.056	-0.077
DR1	9.43	5.18	0.141	0.283
DR2	-0.40	1.68	-0.023	0.084
CR1	-5.44	-6.27	-0.085	-0.065
CR2	4.53	-5.44	0.072	-0.061
PSVR	0.31	0.30	0.018	0.016
ATKP	14.77	15.42	0.285	0.303
ATKN	13.28	7.97	0.268	0.156
CLMP	6.11	4.75	0.263	0.177
CLMN	8.28	5.16	0.261	0.172
PUMP	10.03	0.16	0.305	0.007
PUMN	11.47	-4.02	0.385	-0.140
SMDP	1.06	-3.93	0.052	-0.158
SMDN	6.14	-4.53	0.255	-0.181
EFMP	7.48	4.28	0.248	0.207
EFMN	11.72	1.14	0.345	0.043
LCIP	2.25	2.28	0.258	0.236
LCIN	0.34	-1.75	0.029	-0.171

VARIATE: HSCA (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
QSAT	55.43	89.84	0.239	0.303
VSAT	40.70	37.98	0.158	0.129
HSPC	6.89	2.17	0.324	0.092
HSCA	13.88	14.95	1.000	1.000
HSPS	0.81	3.27	0.041	0.163
ROMA	6.01	10.26	0.114	0.269
ROPS	-8.89	39.28	-0.097	0.306
ALG	6.17	4.28	0.375	0.272
TRIG	1.91	1.59	0.182	0.158
UNIT1	11.22	8.73	0.243	0.302
UNIT2	28.15	18.62	0.313	0.304
UNIT3	17.16	10.09	0.164	0.192
UNIT4	27.75	31.27	0.247	0.375
FINAL	10.28	11.73	0.335	0.438
GEFT2	0.27	0.09	0.032	0.013
GEFT3	-0.06	-0.14	-0.009	-0.027
HPT1	-1.61	-5.37	-0.024	-0.082
HPT2	4.49	-4.31	0.066	-0.069
NS1	2.28	4.75	0.137	0.273
NS2	-1.58	3.73	-0.100	0.221
DP1	-4.40	2.33	-0.101	0.202
DP2	0.82	-0.40	0.071	-0.032
CR1	-0.52	-0.48	-0.012	-0.008
CR2	1.32	-7.05	0.032	-0.125
PSVR	2.02	0.13	0.183	0.011
AIKP	13.29	8.81	0.393	0.274
AIKN	12.55	4.51	0.389	0.139
CLMP	7.17	3.64	0.472	0.214
CLMN	9.51	0.11	0.459	0.006
PUMP	7.42	1.88	0.346	0.131
PUMN	5.52	-0.87	0.284	-0.048
SMDP	2.41	-2.55	0.179	-0.163
SMDN	1.86	-2.72	0.118	-0.172
EFMP	5.68	4.57	0.289	0.349
EFMN	5.22	2.25	0.235	0.135
LCIP	0.88	0.05	0.155	0.008
LCIN	0.44	-0.49	0.058	-0.076

VARIATE: HSPS (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
OSAT	14.71	64.68	0.045	0.163
VSAT	64.21	10.69	0.178	0.027
HSPC	2.19	5.47	0.073	0.172
HSCA	0.81	3.27	0.041	0.163
HSPS	27.43	26.90	1.000	1.000
RQMA	5.91	12.90	0.079	0.252
RQPS	34.65	26.61	0.270	0.155
ALG	4.75	2.07	0.206	0.098
TRIG	4.20	3.38	0.285	0.250
UNIT1	5.23	2.64	0.081	0.068
UNIT2	27.70	13.95	0.219	0.170
UNIT3	27.56	13.10	0.188	0.186
UNIT4	20.90	27.80	0.132	0.249
FINAL	5.71	6.03	0.132	0.168
GEFT2	-0.08	0.66	-0.007	0.067
GEFT3	0.17	-0.17	0.018	-0.024
HPT1	8.86	27.96	0.094	0.319
HPT2	8.21	18.09	0.086	0.216
NS1	-4.00	-2.20	-0.171	-0.094
NS2	-1.63	3.74	-0.073	0.165
DR1	8.82	2.96	0.144	0.191
DR2	-0.73	-1.60	-0.045	-0.094
CR1	11.72	16.01	0.199	0.196
CR2	5.95	8.13	0.104	0.108
PSVR	0.44	0.74	0.028	0.045
AIKP	5.44	6.02	0.114	0.140
ATKN	2.76	2.03	0.061	0.047
CLMP	2.31	4.07	0.108	0.179
CLMN	4.48	0.82	0.154	0.032
PUMP	0.23	4.35	0.007	0.226
PUMN	-0.21	5.39	-0.008	0.221
SMDP	-1.92	-3.03	-0.101	-0.144
SMDN	-2.13	-0.65	-0.096	-0.031
EFMP	1.55	5.48	0.056	0.312
EFMN	0.20	2.49	0.006	0.112
LCIP	-0.18	0.91	-0.023	0.111
LCIN	0.22	1.44	0.021	0.166

VARIATE: ROMA (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
QSAT	157.18	114.68	0.178	0.152
VSAT	53.86	-13.39	0.055	-0.018
HSPC	4.51	-12.38	0.056	-0.205
HSCA	6.01	10.26	0.114	0.269
HSPS	5.91	12.90	0.079	0.252
ROMA	201.61	97.33	1.000	1.000
ROPS	69.04	96.33	0.199	0.294
ALG	14.78	-2.38	0.236	-0.059
TRIG	4.81	-1.50	0.121	-0.058
UNIT1	30.69	-9.50	0.174	-0.129
UNIT2	104.04	5.09	0.303	0.033
UNIT3	100.30	17.57	0.252	0.131
UNIT4	107.02	28.68	0.250	0.135
FINAL	33.23	6.05	0.284	0.089
GEFT2	2.25	-1.64	0.070	-0.088
GEFT3	1.09	-2.05	0.045	-0.154
HPT1	3.49	-16.30	0.014	-0.098
HPT2	-5.60	-17.23	-0.022	-0.108
NS1	-9.30	0.32	-0.146	0.007
NS2	0.21	4.01	0.003	0.093
DR1	-8.15	1.50	-0.049	0.051
DR2	5.27	0.70	0.120	0.022
CR1	8.94	22.30	0.056	0.144
CR2	-30.88	20.37	-0.198	0.142
PSVR	2.33	-0.07	0.056	-0.002
ATKP	60.24	19.91	0.467	0.243
ATKN	54.39	12.95	0.442	0.157
CLMP	25.49	10.80	0.441	0.250
CLMN	31.88	3.05	0.404	0.063
PUMP	27.65	16.68	0.339	0.456
PUMN	27.73	19.28	0.374	0.416
SMDP	5.34	3.03	0.104	0.076
SMDN	10.56	1.06	0.176	0.026
EFMP	22.30	10.84	0.297	0.324
EFMN	26.91	8.71	0.318	0.205
LCIP	2.30	-3.22	0.106	-0.207
LCIN	-9.25	0.09	-0.321	0.006

VARIATE: ROPS (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
QSAT	286.08	578.10	0.188	0.227
VSAT	120.84	-73.16	0.071	-0.029
HSPC	0.19	13.32	0.001	0.066
HSCA	-8.89	39.28	-0.097	0.306
HSPS	34.65	26.61	0.270	0.155
ROMA	69.04	96.33	0.199	0.294
ROPS	599.40	1102.15	1.000	1.000
ALG	14.67	16.08	0.136	0.119
TRIG	19.85	17.91	0.288	0.207
UNIT1	25.90	90.82	0.085	0.366
UNIT2	92.06	74.98	0.156	0.143
UNIT3	48.86	97.39	0.071	0.216
UNIT4	-13.54	251.14	-0.018	0.351
FINAL	48.23	81.08	0.239	0.353
GEFT2	12.33	5.48	0.224	0.087
GEFT3	6.97	0.84	0.165	0.019
HPT1	74.34	47.81	0.169	0.085
HPT2	67.19	52.55	0.151	0.098
NS1	-0.39	-8.88	-0.004	-0.059
NS2	1.19	4.61	0.011	0.032
DR1	-30.47	8.85	-0.107	0.089
DR2	7.58	15.65	0.100	0.144
CR1	-19.61	156.49	-0.071	0.299
CR2	-48.75	75.67	-0.182	0.157
PSVR	20.42	26.58	0.282	0.252
AIKP	-33.39	34.98	-0.150	0.127
AIKN	-1.32	19.62	-0.006	0.071
CLMP	-2.84	3.92	-0.028	0.027
CLMN	-8.75	8.26	-0.064	0.051
PUMP	28.67	56.16	0.204	0.456
PUMN	27.97	61.39	0.219	0.393
SMDP	-15.74	6.06	-0.178	0.045
SMDN	-9.50	10.16	-0.092	0.075
EFMP	17.43	30.80	0.135	0.274
EFMN	28.47	41.63	0.195	0.292
LCIP	-5.70	0.59	-0.153	0.011
LCIN	6.01	-4.15	0.121	-0.074

VARIATE: ALG (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
OSAT	125.40	135.93	0.456	0.436
VSAT	32.75	35.66	0.107	0.115
HSPC	8.33	4.90	0.330	0.197
HSCA	6.17	4.28	0.375	0.272
HSPS	4.75	2.07	0.206	0.098
ROMA	14.78	-2.38	0.236	-0.059
ROPS	14.67	16.08	0.136	0.119
ALG	19.51	16.49	1.000	1.000
TRIG	6.40	5.64	0.515	0.533
UNIT1	30.60	12.77	0.558	0.421
UNIT2	67.30	30.04	0.631	0.467
UNIT3	71.94	16.42	0.581	0.298
UNIT4	75.81	41.08	0.569	0.469
FINAL	21.98	14.27	0.604	0.508
GEFT2	2.96	-0.25	0.299	-0.032
GEFT3	1.79	-0.61	0.236	-0.112
HPT1	13.82	12.16	0.174	0.177
HPT2	17.86	7.31	0.222	0.111
NS1	2.61	3.58	0.132	0.196
NS2	2.31	2.27	0.123	0.128
DR1	-3.13	3.46	-0.061	0.285
DR2	3.84	3.06	0.281	0.231
CR1	9.26	-4.31	0.186	-0.067
CR2	9.45	-14.15	0.195	-0.239
PSVR	1.77	-0.96	0.135	-0.075
ATKP	20.59	9.49	0.513	0.281
ATKN	12.77	8.98	0.334	0.264
CLMP	8.73	1.52	0.485	0.085
CLMN	10.73	3.49	0.437	0.175
PUMP	11.07	1.24	0.436	0.082
PUMN	9.30	1.70	0.403	0.089
SMDP	3.98	1.00	0.249	0.061
SMDN	4.29	0.90	0.230	0.054
EFMP	10.02	3.87	0.429	0.281
EFMN	10.33	0.48	0.392	0.027
LCIP	1.83	0.55	0.271	0.086
LCIN	2.77	0.35	0.309	0.052

VARIATE: TRIG (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
QSAT	50.11	60.58	0.286	0.303
VSAT	25.19	26.42	0.130	0.133
HSPC	2.61	-0.02	0.163	-0.001
HSCA	1.91	1.59	0.182	0.158
HSPS	4.20	3.38	0.285	0.250
ROMA	4.81	-1.50	0.121	-0.058
RQPS	19.85	17.91	0.288	0.207
ALG	6.40	5.64	0.515	0.533
TRIG	7.91	6.78	1.000	1.000
UNIT1	14.09	3.60	0.404	0.185
UNIT2	27.20	19.45	0.401	0.472
UNIT3	30.91	11.41	0.392	0.323
UNIT4	18.25	18.88	0.215	0.336
FINAL	8.66	8.56	0.374	0.475
GEFT2	0.77	0.04	0.122	0.009
GEFT3	0.25	-0.39	0.052	-0.112
HPT1	1.77	3.46	0.035	0.079
HPT2	4.54	-3.62	0.089	-0.086
NS1	1.82	1.83	0.145	0.156
NS2	-0.32	1.07	-0.027	0.094
DR1	-5.42	0.64	-0.165	0.082
DR2	0.52	1.19	0.060	0.139
CR1	2.95	1.22	0.093	0.030
CR2	-0.28	-2.99	-0.009	-0.079
PSVR	1.66	0.81	0.199	0.098
AIKP	4.47	2.47	0.175	0.114
AIKN	3.05	4.54	0.125	0.208
CLMP	2.86	0.57	0.250	0.049
CLMN	3.35	2.18	0.214	0.170
PUMP	5.36	2.91	0.331	0.302
PUMN	5.15	2.16	0.350	0.176
SMDP	2.06	0.30	0.203	0.029
SMDN	2.26	0.04	0.190	0.004
EFMP	1.06	1.41	0.072	0.159
EFMN	3.19	0.15	0.190	0.013
LCIP	1.17	0.35	0.272	0.084
LCIN	1.25	0.41	0.219	0.094

VARIATE: EFMP (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
QSAT	110.75	107.18	0.337	0.412
VSAT	-59.41	5.10	-0.163	0.020
HSPC	7.48	4.28	0.248	0.207
HSCA	5.68	4.57	0.289	0.349
HSPS	1.55	5.48	0.056	0.312
ROMA	22.30	10.84	0.297	0.324
ROPS	17.43	30.80	0.135	0.274
ALG	10.02	3.87	0.429	0.281
TRIG	1.06	1.41	0.072	0.159
UNIT1	17.63	7.38	0.269	0.292
UNIT2	33.79	18.32	0.265	0.341
UNIT3	26.70	13.63	0.180	0.296
UNIT4	50.93	24.74	0.320	0.338
FINAL	13.88	10.01	0.319	0.427
GEFT2	3.04	-0.44	0.256	-0.069
GEFT3	2.89	-0.09	0.317	-0.021
HPT1	16.44	10.46	0.173	0.183
HPT2	8.77	6.03	0.091	0.110
NS1	4.39	0.26	0.185	0.017
NS2	4.30	0.82	0.191	0.056
DR1	10.01	1.45	0.162	0.143
DR2	4.01	2.23	0.245	0.201
CR1	1.57	13.76	0.026	0.258
CR2	0.21	6.31	0.004	0.128
PSVR	-0.74	2.33	-0.048	0.216
AIKP	32.07	22.43	0.668	0.796
AIKN	27.26	15.45	0.595	0.545
CLMP	11.34	9.21	0.527	0.619
CLMN	20.34	8.06	0.692	0.485
PUMP	22.79	5.61	0.750	0.446
PUMN	18.06	4.82	0.654	0.302
SMDP	6.84	-3.63	0.358	-0.264
SMDN	3.54	-0.04	0.158	-0.003
EFMP	27.94	11.49	1.000	1.000
EFMN	25.91	7.96	0.823	0.547
LCIP	1.45	0.65	0.179	0.121
LCIN	0.16	0.93	0.015	0.164

VARIATE: UNIT1 (N = 134; 62 FEMALES AND 72 MALES)

	COVARIANCES		CORRELATIONS	
VARIATE	FEMALES	MALES	FEMALES	MALES
QSAT	392.12	176.86	0.508	0.309
VSAT	143.30	-2.51	0.167	-0.004
HSPC	22.26	9.84	0.314	0.215
HSCA	11.22	8.73	0.243	0.302
HSPS	5.23	2.64	0.081	0.068
RQMA	30.69	-9.50	0.174	-0.129
RQPS	25.90	90.82	0.085	0.366
ALG	30.60	12.77	0.558	0.421
TRIG	14.09	3.60	0.404	0.185
UNIT1	153.87	55.78	1.000	1.000
UNIT2	220.48	46.72	0.736	0.395
UNIT3	251.83	25.56	0.724	0.252
UNIT4	228.15	86.67	0.610	0.538
FINAL	66.34	27.65	0.649	0.535
GEFT2	6.95	1.78	0.249	0.126
GEFT3	5.62	0.74	0.263	0.073
HPT1	20.04	22.55	0.090	0.179
HPT2	0.59	24.01	0.003	0.199
NS1	8.35	3.75	0.150	0.112
NS2	6.32	-0.73	0.119	-0.023
DR1	-25.50	3.69	-0.176	0.165
DR2	8.24	6.49	0.215	0.266
CR1	16.18	13.85	0.116	0.118
CR2	12.46	8.16	0.092	0.075
PSVR	4.58	0.79	0.125	0.033
AIKP	50.69	16.46	0.450	0.265
AIKN	37.73	7.36	0.351	0.118
CLMP	24.57	2.42	0.487	0.074
CLMN	28.89	3.54	0.419	0.097
PUMP	24.05	1.85	0.337	0.067
PUMN	22.85	2.03	0.353	0.058
SMDP	3.81	-1.30	0.085	-0.043
SMDN	2.09	-0.64	0.040	-0.021
EFMP	17.63	7.38	0.269	0.292
EFMN	23.15	7.10	0.313	0.221
LCIP	3.05	2.74	0.161	0.232
LCIN	5.42	-2.68	0.215	-0.214

VARIATE: UNIT2 (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
OSAT	844.47	603.06	0.562	0.496
VSAT	219.86	20.93	0.132	0.017
HSPC	56.82	13.51	0.412	0.139
HSCA	28.15	18.62	0.313	0.304
HSPS	27.70	13.95	0.219	0.170
ROMA	104.04	5.09	0.303	0.033
ROPS	92.06	74.98	0.156	0.143
ALG	67.30	30.04	0.631	0.467
TRIG	27.20	19.45	0.401	0.472
UNIT1	220.48	46.72	0.736	0.395
UNIT2	583.04	251.17	1.000	1.000
UNIT3	465.31	114.38	0.687	0.532
UNIT4	507.14	185.93	0.697	0.544
FINAL	143.43	66.43	0.721	0.606
GEFT2	18.56	2.75	0.342	0.092
GEFT3	10.25	-0.77	0.246	-0.036
HPT1	140.59	62.56	0.324	0.234
HPT2	109.96	57.43	0.250	0.224
NS1	1.56	7.91	0.014	0.111
NS2	10.48	2.84	0.102	0.041
DR1	9.30	4.84	0.033	0.102
DR2	20.87	12.92	0.280	0.249
CR1	47.82	34.98	0.176	0.140
CR2	31.18	14.49	0.118	0.063
PSVR	14.82	0.37	0.208	0.007
ATKP	110.46	29.62	0.504	0.225
ATKN	113.38	25.92	0.542	0.195
CLMP	54.05	2.99	0.550	0.043
CLMN	75.54	4.61	0.563	0.059
PUMP	48.34	13.77	0.348	0.234
PUMN	33.19	1.31	0.303	0.018
SMDP	19.48	-4.83	0.223	-0.075
SMDN	20.95	-10.04	0.205	-0.155
EFMP	33.79	18.32	0.265	0.341
EFMN	44.86	8.53	0.312	0.125
LCIP	10.69	1.24	0.290	0.050
LCIN	11.30	-5.12	0.230	-0.193

VARIATE: UNIT3 (N = 134; 62 FEMALES AND 72 MALES)

	COVARIANCES		CORRELATIONS	
VARIATE	FEMALES	MALES	FEMALES	MALES
OSAT	720.35	268.26	0.412	0.258
VSAT	66.51	-13.78	0.034	-0.013
HSPC	64.04	13.10	0.400	0.158
HSCA	17.16	10.09	0.164	0.192
HSPS	27.56	13.10	0.188	0.186
RQMA	100.30	17.57	0.252	0.131
RQPS	48.86	97.39	0.071	0.216
ALG	71.94	16.42	0.581	0.298
TRIG	30.91	11.41	0.392	0.323
UNIT1	251.83	25.56	0.724	0.252
UNIT2	465.31	114.38	0.687	0.532
UNIT3	786.79	184.30	1.000	1.000
UNIT4	647.97	176.76	0.766	0.604
FINAL	140.36	60.49	0.607	0.644
GEFT2	7.40	1.28	0.117	0.050
GEFT3	6.60	0.39	0.136	0.021
HPT1	87.20	56.83	0.173	0.248
HPT2	20.17	31.24	0.039	0.142
NS1	7.58	-8.16	0.060	-0.134
NS2	9.64	-4.37	0.081	-0.074
DR1	5.70	4.19	0.017	0.103
DR2	22.06	11.53	0.255	0.260
CR1	54.96	1.46	0.174	0.007
CR2	47.23	-1.03	0.153	-0.005
PSVR	0.91	-2.63	0.011	-0.061
AIKP	89.27	23.17	0.350	0.205
AIKN	58.20	24.50	0.239	0.216
CLMP	42.72	10.76	0.374	0.181
CLMN	52.25	5.17	0.335	0.078
PUMP	57.19	5.76	0.355	0.114
PUMN	41.69	-0.34	0.284	-0.005
SMDP	16.60	-6.26	0.164	-0.114
SMDN	17.78	-6.46	0.150	-0.117
EFMP	26.70	13.63	0.180	0.296
EFMN	38.80	4.07	0.232	0.070
LCIP	15.22	2.32	0.356	0.108
LCIN	8.33	0.60	0.146	0.026

VARIATE: UNIT4 (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
QSAT	799.98	469.26	0.426	0.284
VSAT	-143.96	131.38	-0.069	0.080
HSPC	64.11	37.22	0.373	0.282
HSCA	27.75	31.27	0.247	0.375
HSPS	20.90	27.80	0.132	0.249
RQMA	107.02	28.68	0.250	0.135
RQPS	-13.54	251.14	-0.018	0.351
ALG	75.81	41.08	0.569	0.469
TRIG	18.25	18.88	0.215	0.336
UNIT1	228.15	86.67	0.610	0.538
UNIT2	507.14	185.93	0.697	0.544
UNIT3	647.97	176.76	0.766	0.604
UNIT4	908.89	465.17	1.000	1.000
FINAL	172.50	112.63	0.694	0.755
GEFT2	8.81	6.10	0.130	0.150
GEFT3	10.66	-0.06	0.205	-0.002
HPT1	112.04	65.63	0.207	0.180
HPT2	36.83	62.85	0.067	0.180
NS1	3.18	15.03	0.024	0.155
NS2	7.64	6.47	0.059	0.069
DR1	37.46	19.71	0.106	0.306
DR2	21.13	24.01	0.227	0.341
CR1	56.14	9.14	0.166	0.027
CR2	48.18	7.48	0.146	0.024
PSVR	-4.40	-1.95	-0.049	-0.028
ATKP	121.15	39.71	0.443	0.221
AIKN	105.43	3.07	0.404	0.017
CLMP	54.35	0.62	0.443	0.007
CLMN	83.43	-2.80	0.498	-0.026
PUMP	65.24	5.47	0.376	0.068
PUMN	34.42	0.90	0.219	0.009
SMDP	17.62	-5.31	0.162	-0.061
SMDN	17.76	-8.23	0.139	-0.093
EFMP	50.93	24.74	0.320	0.338
EFMN	51.80	8.36	0.288	0.090
LCIP	8.13	4.04	0.177	0.119
LCIN	2.76	2.54	0.045	0.070

VARIATE: FINAL (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
QSAT	225.56	248.95	0.440	0.469
VSAT	119.36	50.96	0.210	0.096
HSPC	12.65	12.03	0.269	0.284
HSCA	10.28	11.73	0.335	0.438
HSPS	5.71	6.03	0.132	0.168
ROMA	33.23	6.05	0.284	0.089
ROPS	48.23	81.08	0.239	0.353
ALG	21.98	14.27	0.604	0.508
TRIG	8.66	8.56	0.374	0.475
UNIT1	66.34	27.65	0.649	0.535
UNIT2	143.43	66.43	0.721	0.606
UNIT3	140.36	60.49	0.607	0.644
UNIT4	172.50	112.63	0.694	0.755
FINAL	67.90	47.89	1.000	1.000
GEFT2	4.16	2.09	0.225	0.160
GEFT3	2.13	0.32	0.150	0.035
HPT1	38.69	13.77	0.261	0.118
HPT2	24.12	10.84	0.161	0.097
NS1	5.32	4.23	0.144	0.136
NS2	7.08	2.74	0.202	0.091
DR1	3.88	6.47	0.040	0.313
DR2	7.32	10.73	0.287	0.474
CR1	16.66	7.12	0.180	0.065
CR2	7.48	4.20	0.083	0.042
PSVR	0.72	1.47	0.029	0.067
AIKP	19.95	23.28	0.267	0.405
AIKN	22.82	16.45	0.320	0.284
CLMP	12.25	6.35	0.365	0.209
CLMN	16.55	6.11	0.361	0.180
PUMP	18.54	2.55	0.391	0.099
PUMN	16.80	-2.52	0.390	-0.077
SMDP	3.44	-3.61	0.116	-0.128
SMDN	9.46	-3.50	0.272	-0.124
EFMP	13.88	10.01	0.319	0.427
EFMN	19.91	4.12	0.405	0.139
LCIP	2.54	0.99	0.202	0.091
LCIN	3.45	-1.58	0.206	-0.136

VARIATE: GEFT2 (N = 134; 62 FEMALES AND 72 MALES)

	COVARIANCES		CORRELATIONS	
VARIATE	FEMALES	MALES	FEMALES	MALES
QSAT	74.45	-0.64	0.532	-0.004
VSAT	13.98	10.47	0.090	0.073
HSPC	1.07	1.53	0.084	0.132
HSCA	0.27	0.09	0.032	0.013
HSPS	-0.08	0.66	-0.007	0.067
ROMA	2.25	-1.64	0.070	-0.088
ROPS	12.33	5.48	0.224	0.087
ALG	2.96	-0.25	0.299	-0.032
TRIG	0.77	0.04	0.122	0.009
UNIT1	6.95	1.78	0.249	0.126
UNIT2	18.56	2.75	0.342	0.092
UNIT3	7.40	1.28	0.117	0.050
UNIT4	8.81	6.10	0.130	0.150
FINAL	4.16	2.09	0.225	0.160
GEFT2	5.04	3.57	1.000	1.000
GEFT3	2.57	1.68	0.663	0.659
HPT1	21.10	6.86	0.522	0.215
HPT2	17.47	5.94	0.427	0.194
NS1	1.70	0.41	0.169	0.048
NS2	2.75	-0.31	0.287	-0.038
DR1	1.53	1.30	0.058	0.229
DR2	2.17	0.22	0.312	0.036
CR1	5.14	1.96	0.204	0.066
CR2	2.86	1.84	0.116	0.067
PSVR	2.70	0.13	0.407	0.021
AIKP	2.23	-0.46	0.109	-0.029
AIKN	3.55	1.57	0.182	0.099
CLMP	1.87	0.72	0.204	0.086
CLMN	2.27	1.18	0.182	0.127
PUMP	1.19	-0.90	0.092	-0.128
PUMN	2.27	0.82	0.193	0.093
SMDP	0.44	-1.02	0.054	-0.133
SMDN	0.95	0.70	0.100	0.091
EFMP	3.04	-0.44	0.256	-0.069
EFMN	3.83	1.30	0.286	0.160
LCIP	1.06	0.75	0.310	0.250
LCIN	0.81	-0.61	0.177	-0.192

VARIATE: GEFT3 (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
QSAT	47.62	-0.36	0.444	-0.003
VSAT	-3.08	14.45	-0.026	0.141
HSPC	-0.18	-0.01	-0.018	-0.001
HSCA	-0.06	-0.14	-0.009	-0.027
HSPS	0.17	-0.17	0.018	-0.024
ROMA	1.09	-2.05	0.045	-0.154
ROPS	6.97	0.84	0.165	0.019
ALG	1.79	-0.61	0.236	-0.112
TRIG	0.25	-0.39	0.052	-0.112
UNIT1	5.62	0.74	0.263	0.073
UNIT2	10.25	-0.77	0.246	-0.036
UNIT3	6.60	0.39	0.136	0.021
UNIT4	10.66	-0.06	0.205	-0.002
FINAL	2.13	0.32	0.150	0.035
GEFT2	2.57	1.68	0.663	0.659
GEFT3	2.97	1.81	1.000	1.000
HPT1	12.62	6.54	0.407	0.288
HPT2	13.49	3.78	0.430	0.173
NS1	0.09	0.30	0.012	0.050
NS2	1.50	-0.89	0.204	-0.152
DR1	0.49	0.29	0.024	0.072
DR2	2.01	-0.14	0.376	-0.031
CR1	4.77	-0.43	0.246	-0.020
CR2	4.46	-0.15	0.236	-0.008
PSVR	1.42	0.31	0.278	0.073
AIKP	1.64	-0.01	0.105	-0.001
AIKN	1.62	1.18	0.109	0.104
CLMP	1.46	1.30	0.209	0.220
CLMN	1.85	1.18	0.193	0.179
PUMP	1.74	-1.22	0.176	-0.244
PUMN	1.90	-0.29	0.211	-0.046
SMDP	1.38	-1.74	0.222	-0.320
SMDN	0.52	0.50	0.071	0.092
EFMP	2.89	-0.09	0.317	-0.021
EFMN	2.41	0.96	0.234	0.166
LCIP	0.55	0.19	0.210	0.089
LCIN	0.19	-0.18	0.055	-0.078

VARIATE: HPT1 (N = 134; 62 FEMALES AND 72 MALES)

	COVARIANCES		CORRELATIONS	
VARIATE	FEMALES	MALES	FEMALES	MALES
QSAT	306.40	154.93	0.274	0.120
VSAT	1.65	-126.52	0.001	-0.098
HSPC	22.67	4.01	0.221	0.039
HSCA	-1.61	-5.37	-0.024	-0.082
HSPS	8.86	27.96	0.094	0.319
RQMA	3.49	-16.30	0.014	-0.098
RQPS	74.34	47.81	0.169	0.085
ALG	13.82	12.16	0.174	0.177
TRIG	1.77	3.46	0.035	0.079
UNIT1	20.04	22.55	0.090	0.179
UNIT2	140.59	62.56	0.324	0.234
UNIT3	87.20	56.83	0.173	0.248
UNIT4	112.04	65.63	0.207	0.180
FINAL	38.69	13.77	0.261	0.118
GEFT2	21.10	6.86	0.522	0.215
GEFT3	12.62	6.54	0.407	0.288
HPT1	323.34	284.88	1.000	1.000
HPT2	259.09	206.06	0.791	0.755
NS1	-9.21	-18.51	-0.115	-0.244
NS2	7.36	2.96	0.096	0.040
DR1	59.72	4.30	0.284	0.085
DR2	10.83	-5.17	0.195	-0.094
CR1	63.07	81.40	0.312	0.306
CR2	74.92	15.97	0.380	0.065
PSVR	8.75	2.12	0.164	0.039
AIKP	28.57	13.32	0.175	0.095
AIKN	24.90	18.93	0.160	0.134
CLMP	14.42	6.19	0.197	0.084
CLMN	18.97	6.36	0.190	0.077
PUMP	9.11	7.52	0.088	0.120
PUMN	19.74	14.74	0.210	0.186
SMDP	1.45	4.52	0.022	0.066
SMDN	4.68	6.35	0.062	0.092
EFMP	16.44	10.46	0.173	0.183
EFMN	19.13	17.48	0.179	0.241
LCIP	9.01	2.23	0.328	0.084
LCIN	5.39	3.11	0.148	0.110

VARIATE: HPT2 (N = 134: 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
QSAT	319.38	146.11	0.282	0.118
VSAT	54.40	6.50	0.043	0.005
HSPC	4.61	9.83	0.044	0.099
HSCA	4.49	-4.31	0.066	-0.069
HSPS	8.21	18.09	0.086	0.216
ROMA	-5.60	-17.23	-0.022	-0.108
ROPS	67.19	52.55	0.151	0.098
ALG	17.86	7.31	0.222	0.111
TRIG	4.54	-3.62	0.089	-0.086
UNIT1	0.59	24.01	0.003	0.199
UNIT2	109.96	57.43	0.250	0.224
UNIT3	20.17	31.24	0.039	0.142
UNIT4	36.83	62.85	0.067	0.180
FINAL	24.12	10.84	0.161	0.097
GEFT2	17.47	5.94	0.427	0.194
GEFT3	13.49	3.78	0.430	0.173
HPT1	259.09	206.06	0.791	0.755
HPT2	331.71	261.69	1.000	1.000
NS1	-19.49	-8.41	-0.239	-0.116
NS2	8.59	5.41	0.111	0.077
DR1	27.39	6.32	0.129	0.131
DR2	12.90	4.02	0.229	0.076
CR1	65.11	57.54	0.318	0.226
CR2	59.23	22.72	0.296	0.096
PSVR	14.35	2.17	0.266	0.042
AIKP	1.13	-2.40	0.007	-0.018
AIKN	9.18	10.18	0.058	0.075
CLMP	6.84	-0.66	0.092	-0.009
CLMN	4.27	3.37	0.042	0.042
PUMP	6.51	1.74	0.062	0.029
PUMN	6.01	3.26	0.063	0.043
SMDP	-0.57	5.30	-0.009	0.081
SMDN	-3.88	1.14	-0.050	0.017
EFMP	8.77	6.03	0.091	0.110
EFMN	-1.37	9.20	-0.017	0.132
LCIP	7.83	2.91	0.282	0.114
LCIN	13.90	-2.43	0.376	-0.089

VARIATE: NS1 (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
QSAT	79.21	74.02	0.284	0.215
VSAT	62.03	120.99	0.201	0.352
HSPC	1.97	-2.07	0.077	-0.075
HSCA	2.28	4.75	0.137	0.273
HSPS	-4.00	-2.20	-0.171	-0.094
ROMA	-9.30	0.32	-0.146	0.007
ROPS	-0.39	-8.88	-0.004	-0.059
ALG	2.61	3.58	0.132	0.196
TRIG	1.82	1.83	0.145	0.156
UNIT1	8.35	3.75	0.150	0.112
UNIT2	1.56	7.91	0.014	0.111
UNIT3	7.58	-8.16	0.060	-0.134
UNIT4	3.18	15.03	0.024	0.155
FINAL	5.32	4.23	0.144	0.136
GEFT2	1.70	0.41	0.169	0.048
GEFT3	0.09	0.30	0.012	0.050
HPT1	-9.21	-18.51	-0.115	-0.244
HPT2	-19.49	-8.41	-0.239	-0.116
NS1	20.02	20.24	1.000	1.000
NS2	5.34	7.50	0.280	0.383
DR1	3.88	4.78	0.074	0.355
DR2	5.26	3.60	0.381	0.245
CR1	-3.33	-21.87	-0.066	-0.309
CR2	-0.20	-9.46	-0.004	-0.144
PSVR	1.07	-1.95	0.081	-0.136
AIKP	2.22	-0.30	0.055	-0.008
AIKN	3.11	2.45	0.080	0.065
CLMP	1.22	0.48	0.067	0.025
CLMN	3.20	3.16	0.129	0.143
PUMP	4.59	-1.56	0.178	-0.094
PUMN	6.99	-2.04	0.299	-0.096
SMDP	0.67	-4.33	0.041	-0.237
SMDN	3.97	-3.94	0.210	-0.215
EFMP	4.39	0.26	0.185	0.017
EFMN	7.28	-1.30	0.273	-0.067
LCIP	0.17	-0.84	0.025	-0.118
LCIN	0.81	-0.20	0.089	-0.026

VARIATE: NS2 (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
QSAT	97.28	65.98	0.366	0.198
VSAT	94.75	61.90	0.322	0.186
HSPC	-1.36	-2.04	-0.056	-0.077
HSCA	-1.58	3.73	-0.100	0.221
HSPS	-1.63	3.74	-0.073	0.165
RQMA	0.21	4.01	0.003	0.093
RQPS	1.19	4.61	0.011	0.032
ALG	2.31	2.27	0.123	0.128
TRIG	-0.32	1.07	-0.027	0.094
UNIT1	6.32	-0.73	0.119	-0.023
UNIT2	10.48	2.84	0.102	0.041
UNIT3	9.64	-4.37	0.081	-0.074
UNIT4	7.64	6.47	0.059	0.069
FINAL	7.08	2.74	0.202	0.091
GEFT2	2.75	-0.31	0.287	-0.038
GEFT3	1.50	-0.89	0.204	-0.152
HPT1	7.36	2.96	0.096	0.040
HPT2	8.59	5.41	0.111	0.077
NS1	5.34	7.50	0.280	0.383
NS2	18.18	18.96	1.000	1.000
DR1	9.60	3.18	0.193	0.244
DR2	4.57	0.86	0.347	0.060
CF1	11.28	8.28	0.235	0.121
CF2	11.41	0.33	0.244	0.005
PSVR	1.20	1.04	0.096	0.075
ATKP	-1.48	0.24	-0.038	0.007
ATKN	3.01	0.69	0.081	0.019
CLMP	-0.78	2.13	-0.045	0.111
CLMN	1.56	1.78	0.066	0.084
PUMP	1.80	1.72	0.074	0.106
PUMN	1.64	0.82	0.074	0.040
SMDP	1.37	1.37	0.089	0.078
SMDN	2.97	-1.03	0.165	-0.058
EFMP	4.30	0.82	0.191	0.056
EFMN	3.97	-0.01	0.156	0.000
LCIP	0.26	0.20	0.040	0.029
LCIN	3.71	0.39	0.429	0.053

VARIATE: DR1 (N = 134; 62 FEMALES AND 72 MALES)

	COVARIANCES		CORRELATIONS	
VARIATE	FEMALES	MALES	FEMALES	MALES
QSAT	29.84	69.62	0.041	0.304
VSAT	-67.18	95.00	-0.083	0.416
HSPC	9.43	5.18	0.141	0.283
HSCA	-4.40	2.33	-0.101	0.202
HSPS	8.82	2.96	0.144	0.191
RQMA	-8.15	1.50	-0.049	0.051
RQPS	-30.47	8.85	-0.107	0.089
ALG	-3.13	3.46	-0.061	0.285
TRIG	-5.42	0.64	-0.165	0.082
UNIT1	-25.50	3.69	-0.176	0.165
UNIT2	9.30	4.84	0.033	0.102
UNIT3	5.70	4.19	0.017	0.103
UNIT4	37.46	19.71	0.106	0.306
FINAL	3.88	6.47	0.040	0.313
GEFT2	1.53	1.30	0.058	0.229
GEFT3	0.49	0.29	0.024	0.072
HPT1	59.72	4.30	0.284	0.085
HPT2	27.39	6.32	0.129	0.131
NS1	3.88	4.78	0.074	0.355
NS2	9.60	3.18	0.193	0.244
DR1	136.48	8.94	1.000	1.000
DR2	-0.40	5.32	-0.011	0.545
CR1	28.31	-6.55	0.219	-0.139
CR2	26.33	-6.38	0.205	-0.147
PSVP	-3.39	0.63	-0.098	0.066
AIKP	7.26	0.59	0.068	0.024
ATKN	8.12	1.23	0.080	0.049
CLMP	0.62	0.81	0.013	0.062
CLMN	6.51	1.23	0.100	0.084
PUMP	10.57	1.50	0.157	0.135
PUMN	10.31	1.57	0.169	0.112
SMDP	6.59	-1.64	0.156	-0.135
SMDN	5.10	1.44	0.103	0.118
EFMP	10.01	1.45	0.162	0.143
EFMN	8.38	1.18	0.120	0.092
LCIP	-0.48	0.63	-0.027	0.133
LCIN	-4.76	-0.19	-0.201	-0.038

VARIATE: DR2 (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
OSAT	103.37	90.16	0.537	0.360
VSAT	50.86	56.33	0.238	0.226
HSPC	-0.40	1.68	-0.023	0.084
HSCA	0.82	-0.40	0.071	-0.032
HSPS	-0.73	-1.60	-0.045	-0.094
ROMA	5.27	0.70	0.120	0.022
ROPS	7.58	15.65	0.100	0.144
ALG	3.84	3.06	0.281	0.231
TRIG	0.52	1.19	0.060	0.139
UNIT1	8.24	6.49	0.215	0.266
UNIT2	20.87	12.92	0.280	0.249
UNIT3	22.06	11.53	0.255	0.260
UNIT4	21.13	24.01	0.227	0.341
FINAL	7.32	10.73	0.287	0.474
GEFT2	2.17	0.22	0.312	0.036
GEFT3	2.01	-0.14	0.376	-0.031
HPT1	10.83	-5.17	0.195	-0.094
HPT2	12.90	4.02	0.229	0.076
NS1	5.26	3.60	0.381	0.245
NS2	4.57	0.86	0.347	0.060
DR1	-0.40	5.32	-0.011	0.545
DR2	9.55	10.68	1.000	1.000
CR1	1.32	2.00	0.038	0.039
CR2	1.79	6.28	0.053	0.132
PSVR	0.78	0.86	0.085	0.083
AIKP	2.85	4.78	0.102	0.176
AIKN	6.26	5.39	0.234	0.197
CLMP	2.00	1.53	0.159	0.107
CLMN	4.88	4.42	0.284	0.276
PUMP	3.28	2.14	0.185	0.176
PUMN	4.11	-0.04	0.254	-0.003
SMDP	0.90	-1.42	0.081	-0.107
SMDN	3.69	1.30	0.283	0.098
EFMP	4.01	2.23	0.245	0.201
EFMN	4.45	2.23	0.242	0.159
LCIP	1.14	0.24	0.243	0.046
LCIN	2.42	-0.16	0.386	-0.030

VARIATE: CR1 (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
OSAT	45.80	87.65	0.065	0.073
VSAT	166.14	-219.58	0.214	-0.183
HSPC	-5.44	-6.27	-0.085	-0.065
HSCA	-0.52	-0.48	-0.012	-0.008
HSPS	11.72	16.01	0.199	0.196
ROMA	8.94	22.30	0.056	0.144
ROPS	-19.61	156.49	-0.071	0.299
ALG	9.26	-4.31	0.186	-0.067
TRIG	2.95	1.22	0.093	0.030
UNIT1	16.18	13.85	0.116	0.118
UNIT2	47.82	34.98	0.176	0.140
UNIT3	54.96	1.46	0.174	0.007
UNIT4	56.14	9.14	0.166	0.027
FINAL	16.66	7.12	0.180	0.065
GEFT2	5.14	1.96	0.204	0.066
GEFT3	4.77	-0.43	0.246	-0.020
HPT1	63.07	81.40	0.312	0.306
HPT2	65.11	57.54	0.318	0.226
NS1	-3.33	-21.87	-0.066	-0.309
NS2	11.28	8.28	0.235	0.121
DR1	28.81	-6.55	0.219	-0.139
DR2	1.32	2.00	0.038	0.039
CR1	126.41	248.09	1.000	1.000
CR2	75.38	174.15	0.611	0.759
PSVR	3.73	15.93	0.112	0.318
AIKP	14.00	18.47	0.137	0.141
AIKN	0.31	1.76	0.003	0.013
CLMP	5.92	0.39	0.129	0.006
CLMN	7.82	-0.78	0.125	-0.010
PUMP	2.36	16.28	0.037	0.278
PUMN	4.13	17.08	0.070	0.231
SMDP	6.58	8.58	0.162	0.134
SMDN	6.56	12.84	0.138	0.200
EFMP	1.57	13.76	0.026	0.258
EFMN	-0.57	22.02	-0.008	0.325
LCIP	2.54	-1.96	0.148	-0.079
LCIN	0.34	-0.90	0.037	-0.034

VARIATE: CR2 (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
OSAT	55.42	101.15	0.081	0.091
VSAT	-14.42	-136.89	-0.019	-0.123
HSPC	4.53	-5.44	0.072	-0.061
HSCA	1.32	-7.05	0.032	-0.125
HSPS	5.95	8.13	0.104	0.108
ROMA	-30.88	20.37	-0.198	0.142
ROPS	-48.75	75.67	-0.182	0.157
ALG	9.45	-14.15	0.195	-0.239
TRIG	-0.28	-2.99	-0.009	-0.079
UNIT1	12.46	8.16	0.092	0.075
UNIT2	31.18	14.49	0.118	0.063
UNIT3	47.23	-1.03	0.153	-0.005
UNIT4	48.18	7.48	0.146	0.024
FINAL	7.48	4.20	0.083	0.042
GEFT2	2.86	1.84	0.116	0.067
GEFT3	4.46	-0.15	0.236	-0.008
HPT1	74.92	15.97	0.380	0.065
HPT2	59.23	22.72	0.296	0.096
NS1	-0.20	-9.46	-0.004	-0.144
NS2	11.41	0.33	0.244	0.005
DR1	26.33	-6.38	0.205	-0.147
DR2	1.79	6.28	0.053	0.132
CR1	75.38	174.15	0.611	0.759
CR2	120.34	211.97	1.000	1.000
PSVR	3.13	15.23	0.097	0.329
AIKP	16.49	-0.86	0.166	-0.007
AIKN	11.88	-19.57	0.125	-0.161
CLMP	4.68	-7.35	0.105	-0.115
CLMN	11.04	-4.30	0.181	-0.060
PUMP	2.66	7.73	0.042	0.143
PUMN	4.82	4.64	0.084	0.068
SMDP	3.82	0.42	0.097	0.007
SMDN	2.73	4.53	0.059	0.076
EFMP	0.21	6.31	0.004	0.128
EFMN	0.10	12.77	0.002	0.204
LCTP	4.54	-1.54	0.271	-0.067
LCIN	6.00	-4.15	0.269	-0.170

VARIATE: PSVR (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
QSAT	82.09	66.33	0.446	0.272
VSAT	43.59	39.13	0.214	0.161
HSPC	0.31	0.30	0.018	0.016
HSCA	2.02	0.13	0.183	0.011
HSPS	0.44	0.74	0.028	0.045
ROMA	2.33	-0.07	0.056	-0.002
RQPS	20.42	26.58	0.282	0.252
ALG	1.77	-0.96	0.135	-0.075
TRIG	1.66	0.81	0.199	0.098
UNIT1	4.58	0.79	0.125	0.033
UNIT2	14.82	0.37	0.208	0.007
UNIT3	0.91	-2.63	0.011	-0.061
UNIT4	-4.40	-1.95	-0.049	-0.028
FINAL	0.72	1.47	0.029	0.067
GEFT2	2.70	0.13	0.407	0.021
GEFT3	1.42	0.31	0.278	0.073
HPT1	8.75	2.12	0.164	0.039
HPT2	14.35	2.17	0.266	0.042
NS1	1.07	-1.95	0.081	-0.136
NS2	1.20	1.04	0.096	0.075
DR1	-3.39	0.63	-0.098	0.066
DR2	0.78	0.86	0.085	0.083
CR1	3.73	15.93	0.112	0.318
CR2	3.13	15.23	0.097	0.329
PSVR	8.74	10.12	1.000	1.000
ATKP	0.24	4.82	0.009	0.182
AIKN	1.74	3.42	0.068	0.128
CLMP	3.43	2.72	0.285	0.195
CLMN	2.00	2.41	0.122	0.154
PUMP	0.12	2.81	0.007	0.238
PUMN	2.75	1.41	0.178	0.094
SMDP	-0.42	-1.59	-0.039	-0.123
SMDN	1.09	0.39	0.087	0.030
EFMP	-0.74	2.33	-0.048	0.216
EFMN	1.19	0.75	0.068	0.055
LCIP	0.66	-0.07	0.146	-0.014
LCIN	1.10	-0.48	0.182	-0.089

VARIATE: AIKP (N = 134; 62 FEMALES AND 72 MALES)

	COVARIANCES		CORRELATIONS	
VARIATE	FEMALES	MALES	FEMALES	MALES
QSAT	186.60	243.98	0.330	0.383
VSAT	-85.53	-66.26	-0.136	-0.104
HSPC	14.77	15.42	0.285	0.303
HSCA	13.29	8.81	0.393	0.274
HSPS	5.44	6.02	0.114	0.140
ROMA	60.24	19.91	0.467	0.243
ROPS	-33.39	34.98	-0.150	0.127
ALG	20.59	9.49	0.513	0.281
TRIG	4.47	2.47	0.175	0.114
UNIT1	50.69	16.46	0.450	0.265
UNIT2	110.46	29.62	0.504	0.225
UNIT3	89.27	23.17	0.350	0.205
UNIT4	121.15	39.71	0.443	0.221
FINAL	19.95	23.28	0.267	0.405
GEFT2	2.23	-0.46	0.109	-0.029
GEFT3	1.64	-0.01	0.105	-0.001
HPT1	28.57	13.32	0.175	0.095
HPT2	1.13	-2.40	0.007	-0.018
NS1	2.22	-0.30	0.055	-0.008
NS2	-1.48	0.24	-0.038	0.007
DR1	7.26	0.59	0.068	0.024
DR2	2.85	4.78	0.102	0.176
CR1	14.00	18.47	0.137	0.141
CR2	16.49	-0.86	0.166	-0.007
PSVR	0.24	4.82	0.009	0.182
AIKP	82.45	69.15	1.000	1.000
AIKN	57.66	49.20	0.733	0.707
CLMP	29.20	28.30	0.790	0.776
CLMN	38.29	24.85	0.758	0.610
PUMP	27.60	13.02	0.528	0.422
PUMN	26.35	13.17	0.555	0.337
SMDP	12.89	-6.82	0.393	-0.202
SMDN	6.45	1.01	0.168	0.030
EFMP	32.07	22.43	0.668	0.796
EFMN	31.66	21.27	0.585	0.595
LCIP	4.77	0.45	0.344	0.034
LCIN	-0.99	1.68	-0.054	0.120

VARIATE: AIKN (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES		CORRELATIONS	
	FEMALES	MALES	FEMALES	MALES
OSAT	226.17	272.17	0.419	0.424
VSAT	-102.13	41.92	-0.171	0.066
HSPC	13.28	7.97	0.268	0.156
HSCA	12.55	4.51	0.389	0.139
HSPS	2.76	2.03	0.061	0.047
RQMA	54.39	12.95	0.442	0.157
RQPS	-1.32	19.62	-0.006	0.071
ALG	12.77	8.98	0.334	0.264
TRIG	3.05	4.54	0.125	0.208
UNIT1	37.73	7.36	0.351	0.118
UNIT2	113.38	25.92	0.542	0.195
UNIT3	58.20	24.50	0.239	0.216
UNIT4	105.43	3.07	0.404	0.017
FINAL	22.82	16.45	0.320	0.284
GEFT2	3.55	1.57	0.182	0.099
GEFT3	1.62	1.18	0.109	0.104
HPT1	24.90	18.93	0.160	0.134
HPT2	9.18	10.18	0.058	0.075
NS1	3.11	2.45	0.080	0.065
NS2	3.01	0.69	0.081	0.019
DR1	8.12	1.23	0.080	0.049
DR2	6.26	5.39	0.234	0.197
CR1	0.31	1.76	0.003	0.013
CR2	11.88	-19.57	0.125	-0.161
PSVR	1.74	3.42	0.068	0.128
AIKP	57.66	49.20	0.733	0.707
AIKN	75.08	70.02	1.000	1.000
CLMP	22.10	25.68	0.626	0.699
CLMN	44.08	35.34	0.915	0.862
PUMP	27.83	11.67	0.558	0.376
PUMN	24.32	13.45	0.537	0.342
SMDP	3.87	-4.90	0.124	-0.144
SMDN	12.30	2.35	0.336	0.069
EFMP	27.26	15.45	0.595	0.545
EFMN	35.73	16.68	0.692	0.464
LCIP	3.74	2.32	0.283	0.176
LCIN	0.64	2.51	0.036	0.178

VARIATE: CLMP (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
QSAT	108.51	85.22	0.428	0.253
VSAT	1.06	29.70	0.004	0.089
HSPC	6.11	4.75	0.263	0.177
HSCA	7.17	3.64	0.472	0.214
HSPS	2.31	4.07	0.108	0.179
ROMA	25.49	10.80	0.441	0.250
ROPS	-2.84	3.92	-0.028	0.027
ALG	8.73	1.52	0.485	0.085
TRIG	2.86	0.57	0.250	0.049
UNIT1	24.57	2.42	0.487	0.074
UNIT2	54.05	2.99	0.550	0.043
UNIT3	42.72	10.76	0.374	0.181
UNIT4	54.35	0.62	0.443	0.007
FINAL	12.25	6.35	0.365	0.209
GEFT2	1.87	0.72	0.204	0.086
GEFT3	1.46	1.30	0.209	0.220
HPT1	14.42	6.19	0.197	0.084
HPT2	6.84	-0.66	0.092	-0.009
NS1	1.22	0.48	0.067	0.025
NS2	-0.78	2.13	-0.045	0.111
DR1	0.62	0.81	0.013	0.062
DR2	2.00	1.53	0.159	0.107
CR1	5.92	0.39	0.129	0.006
CR2	4.68	-7.35	0.105	-0.115
PSVR	3.43	2.72	0.285	0.195
AIKP	29.20	28.30	0.790	0.776
AIKN	22.10	25.68	0.626	0.699
CLMP	16.58	19.25	1.000	1.000
CLMN	15.47	14.89	0.683	0.692
PUMP	10.12	6.14	0.432	0.377
PUMN	10.12	7.40	0.476	0.359
SMDP	4.33	-3.84	0.295	-0.216
SMDN	2.60	2.49	0.151	0.139
EFMP	11.34	9.21	0.527	0.619
EFMN	10.96	8.72	0.452	0.462
LCIP	2.31	1.07	0.371	0.154
LCIN	-0.69	0.54	-0.083	0.073

VARIATE: CLMN (N = 134; 62 FEMALES AND 72 MALES)

	COVARIANCES		CORRELATIONS	
VARIATE	FEMALES	MALES	FEMALES	MALES
QSAT	178.09	156.16	0.514	0.415
VSAT	-23.19	88.29	-0.060	0.236
HSPC	8.28	5.16	0.261	0.172
HSCA	9.51	0.11	0.459	0.006
HSPS	4.48	0.82	0.154	0.032
ROMA	31.88	3.05	0.404	0.063
ROPS	-8.75	8.26	-0.064	0.051
ALG	10.73	3.49	0.437	0.175
TRIG	3.35	2.18	0.214	0.170
UNIT1	28.89	3.54	0.419	0.097
UNIT2	75.54	4.61	0.563	0.059
UNIT3	52.25	5.17	0.335	0.078
UNIT4	83.43	-2.80	0.498	-0.026
FINAL	16.55	6.11	0.361	0.180
GEFT2	2.27	1.18	0.182	0.127
GEFT3	1.85	1.18	0.193	0.179
HPT1	18.97	6.36	0.190	0.077
HPT2	4.27	3.37	0.042	0.042
NS1	3.20	3.16	0.129	0.143
NS2	1.56	1.78	0.066	0.084
DR1	6.51	1.23	0.100	0.084
DR2	4.88	4.42	0.284	0.276
CR1	7.82	-0.78	0.125	-0.010
CR2	11.04	-4.30	0.181	-0.060
PSVR	2.00	2.41	0.122	0.154
AIKP	38.29	24.85	0.758	0.610
AIKN	44.08	35.34	0.915	0.862
CLMP	15.47	14.89	0.683	0.692
CLMN	30.92	24.03	1.000	1.000
PUMP	20.19	6.69	0.631	0.368
PUMN	16.66	7.24	0.573	0.314
SMDP	5.75	-3.01	0.286	-0.151
SMDN	9.11	2.92	0.388	0.146
EFMP	20.34	8.06	0.692	0.485
EFMN	24.44	10.18	0.738	0.483
LCIP	3.37	1.02	0.397	0.131
LCIN	0.26	0.63	0.023	0.077

VARIATE: PUMP (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
QSAT	113.06	79.24	0.316	0.278
VSAT	-62.29	-15.01	-0.157	-0.053
HSPC	10.03	0.16	0.305	0.007
HSCA	7.42	1.88	0.346	0.131
HSPS	0.23	4.35	0.007	0.226
ROMA	27.65	16.68	0.339	0.456
ROPS	28.67	56.16	0.204	0.456
ALG	11.07	1.24	0.436	0.082
TRIG	5.36	2.91	0.331	0.302
UNIT1	24.05	1.85	0.337	0.067
UNIT2	48.34	13.77	0.348	0.234
UNIT3	57.19	5.76	0.355	0.114
UNIT4	65.24	5.47	0.376	0.068
FINAL	18.54	2.55	0.391	0.099
GEFT2	1.19	-0.90	0.092	-0.128
GEFT3	1.74	-1.22	0.176	-0.244
HPT1	9.11	7.52	0.088	0.120
HPT2	6.51	1.74	0.062	0.029
NS1	4.59	-1.56	0.178	-0.094
NS2	1.80	1.72	0.074	0.106
DR1	10.57	1.50	0.157	0.135
DR2	3.28	2.14	0.185	0.176
CR1	2.36	16.28	0.037	0.278
CR2	2.66	7.73	0.042	0.143
PSVR	0.12	2.81	0.007	0.238
ALKP	27.60	13.02	0.528	0.422
ALKN	27.83	11.67	0.558	0.376
CLMP	10.12	6.14	0.432	0.377
CLMN	20.19	6.69	0.631	0.368
PUMP	33.07	13.78	1.000	1.000
PUMN	23.29	13.31	0.775	0.762
SMDP	9.84	1.72	0.474	0.114
SMDN	5.83	2.92	0.240	0.193
EFMP	22.79	5.61	0.750	0.446
EFMN	22.81	7.11	0.666	0.446
LCIP	1.17	0.06	0.133	0.010
LCIN	-1.59	0.88	-0.136	0.141

VARIATE: PUMN (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
OSAT	102.70	40.71	0.316	0.113
VSAT	-59.46	-21.44	-0.165	-0.060
HSPC	11.47	-4.02	0.385	-0.140
HSCA	5.52	-0.87	0.284	-0.048
HSPS	-0.21	5.39	-0.008	0.221
ROMA	27.73	19.28	0.374	0.416
ROPS	27.97	61.39	0.219	0.393
ALG	9.30	1.70	0.403	0.089
TRIG	5.15	2.16	0.350	0.176
UNIT1	22.85	2.03	0.353	0.058
UNIT2	38.19	1.31	0.303	0.018
UNIT3	41.69	-0.34	0.284	-0.005
UNIT4	34.42	0.90	0.219	0.009
FINAL	16.80	-2.52	0.390	-0.077
GEFT2	2.27	0.82	0.193	0.093
GEFT3	1.90	-0.29	0.211	-0.046
HPT1	19.74	14.74	0.210	0.186
HPT2	6.01	3.26	0.063	0.043
NS1	6.99	-2.04	0.299	-0.096
NS2	1.64	0.82	0.074	0.040
DR1	10.31	1.57	0.169	0.112
DR2	4.11	-0.04	0.254	-0.003
CR1	4.13	17.08	0.070	0.231
CR2	4.82	4.64	0.084	0.068
PSVR	2.75	1.41	0.178	0.094
AIKP	26.35	13.17	0.555	0.337
ATKN	24.32	13.45	0.537	0.342
CLMP	10.12	7.40	0.476	0.359
CLMN	16.66	7.24	0.573	0.314
PUMP	23.29	13.31	0.775	0.762
PUMN	27.30	22.12	1.000	1.000
SMDP	5.96	3.26	0.316	0.171
SMDN	11.05	8.25	0.501	0.430
EFMP	18.06	4.82	0.654	0.302
EFMN	25.15	12.47	0.808	0.617
LCIP	1.88	0.40	0.236	0.053
LCIN	-1.52	1.41	-0.144	0.179

VARIATE: SMDP (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
OSAT	28.16	-60.40	0.125	-0.194
VSAT	-12.23	-30.42	-0.049	-0.098
HSPC	1.06	-3.93	0.052	-0.158
HSCA	2.41	-2.55	0.179	-0.163
HSPS	-1.92	-3.03	-0.101	-0.144
ROMA	5.34	3.03	0.104	0.076
ROPS	-15.74	6.06	-0.178	0.045
ALG	3.98	1.00	0.249	0.061
TRIG	2.06	0.30	0.203	0.029
UNIT1	3.81	-1.30	0.085	-0.043
UNIT2	19.48	-4.83	0.223	-0.075
UNIT3	16.60	-6.26	0.164	-0.114
UNIT4	17.62	-5.31	0.162	-0.061
FINAL	3.44	-3.61	0.116	-0.128
GEFT2	0.44	-1.02	0.054	-0.133
GEFT3	1.38	-1.74	0.222	-0.320
HPT1	1.45	4.52	0.022	0.066
HPT2	-0.57	5.30	-0.009	0.081
NS1	0.67	-4.33	0.041	-0.237
NS2	1.37	1.37	0.089	0.078
DR1	6.59	-1.64	0.156	-0.135
DR2	0.90	-1.42	0.081	-0.107
CR1	6.58	8.58	0.162	0.134
CR2	3.82	0.42	0.097	0.007
PSVR	-0.42	-1.59	-0.039	-0.123
AIKP	12.89	-6.82	0.393	-0.202
AIKN	3.87	-4.90	0.124	-0.144
CLMP	4.33	-3.84	0.295	-0.216
CLMN	5.75	-3.01	0.286	-0.151
PUMP	9.84	1.72	0.474	0.114
PUMN	5.96	3.26	0.316	0.171
SMDP	13.03	16.46	1.000	1.000
SMDN	5.90	9.83	0.387	0.594
EFMP	6.84	-3.63	0.358	-0.264
EFMN	6.55	-0.29	0.304	-0.016
LCIP	1.66	0.44	0.301	0.069
LCIN	-0.55	0.09	-0.074	0.013

VARIATE: SMDN (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
QSAT	57.69	-18.12	0.219	-0.058
VSAT	0.05	57.46	0.000	0.184
HSPC	6.14	-4.53	0.255	-0.181
HSCA	1.86	-2.72	0.118	-0.172
HSPS	-2.13	-0.65	-0.096	-0.031
RQMA	10.56	1.06	0.176	0.026
RQPS	-9.50	10.16	-0.092	0.075
ALG	4.29	0.90	0.230	0.054
TRIG	2.26	0.04	0.190	0.004
UNIT1	2.09	-0.64	0.040	-0.021
UNIT2	20.95	-10.04	0.205	-0.155
UNIT3	17.78	-6.46	0.150	-0.117
UNIT4	17.76	-8.23	0.139	-0.093
FINAL	9.46	-3.50	0.272	-0.124
GEFT2	0.95	0.70	0.100	0.091
GEFT3	0.52	0.50	0.071	0.092
HPT1	4.68	6.35	0.062	0.092
HPT2	-3.88	1.14	-0.050	0.017
NS1	3.97	-3.94	0.210	-0.215
NS2	2.97	-1.03	0.165	-0.058
DR1	5.10	1.44	0.103	0.118
DR2	3.69	1.30	0.283	0.098
CR1	6.56	12.84	0.138	0.200
CR2	2.73	4.53	0.059	0.076
PSVR	1.09	0.39	0.087	0.030
AIKP	6.45	1.01	0.168	0.030
ATKN	12.30	2.35	0.336	0.069
CLMP	2.60	2.49	0.151	0.139
CLMN	9.11	2.92	0.388	0.146
PUMP	5.83	2.92	0.240	0.193
PUMN	11.05	8.25	0.501	0.430
SMDP	5.90	9.83	0.387	0.594
SMDN	17.85	16.67	1.000	1.000
EFMP	3.54	-0.04	0.158	-0.003
EFMN	13.10	6.83	0.521	0.389
LCIP	2.88	0.85	0.447	0.131
LCIN	0.25	0.78	0.029	0.113

VARIATE: EFMN (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
QSAT	116.95	80.08	0.315	0.243
VSAT	-82.37	11.71	-0.200	0.036
HSPC	11.72	1.14	0.345	0.043
HSCA	5.22	2.25	0.235	0.135
HSPS	0.20	2.49	0.006	0.112
ROMA	26.91	8.71	0.318	0.205
ROPS	28.47	41.63	0.195	0.292
ALG	10.33	0.48	0.392	0.027
TRIG	3.19	0.15	0.190	0.013
UNIT1	23.15	7.10	0.313	0.221
UNIT2	44.86	8.53	0.312	0.125
UNIT3	38.80	4.07	0.232	0.070
UNIT4	51.80	8.36	0.288	0.090
FINAL	19.91	4.12	0.405	0.139
GEFT2	3.83	1.30	0.286	0.160
GEFT3	2.41	0.96	0.234	0.166
HPT1	19.13	17.48	0.179	0.241
HPT2	-1.87	9.20	-0.017	0.132
NS1	7.28	-1.30	0.273	-0.067
NS2	3.97	-0.01	0.156	0.000
DR1	8.38	1.18	0.120	0.092
DR2	4.45	2.23	0.242	0.159
CR1	-0.57	22.02	-0.008	0.325
CR2	0.10	12.77	0.002	0.204
PSVR	1.19	0.75	0.068	0.055
AIKP	31.66	21.27	0.585	0.595
AIKN	35.73	16.68	0.692	0.464
CLMP	10.96	8.72	0.452	0.462
CLMN	24.44	10.18	0.738	0.483
PUMP	22.81	7.11	0.666	0.446
PUMN	25.15	12.47	0.808	0.617
SMDP	6.55	-0.29	0.304	-0.016
SMDN	13.10	6.83	0.521	0.389
EFMP	25.91	7.96	0.823	0.547
EFMN	35.50	18.46	1.000	1.000
LCIP	2.41	-0.15	0.265	-0.022
LCIN	-0.67	-0.07	-0.056	-0.010

VARIATE: LCIP (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
QSAT	32.34	-9.55	0.340	-0.079
VSAT	-11.79	-14.53	-0.112	-0.120
HSPC	2.25	2.28	0.258	0.236
HSCA	0.88	0.05	0.155	0.008
HSPS	-0.18	0.91	-0.023	0.111
ROMA	2.30	-3.22	0.106	-0.207
ROPS	-5.70	0.59	-0.153	0.011
ALG	1.83	0.55	0.271	0.086
TRIG	1.17	0.35	0.272	0.084
UNIT1	3.05	2.74	0.161	0.232
UNIT2	10.69	1.24	0.290	0.050
UNIT3	15.22	2.32	0.356	0.108
UNIT4	8.13	4.04	0.177	0.119
FINAL	2.54	0.99	0.202	0.091
GEFT2	1.06	0.75	0.310	0.250
GEFT3	0.55	0.19	0.210	0.089
HPT1	9.01	2.23	0.328	0.084
HPT2	7.83	2.91	0.282	0.114
NS1	0.17	-0.84	0.025	-0.118
NS2	0.26	0.20	0.040	0.029
DR1	-0.48	0.63	-0.027	0.133
DR2	1.14	0.24	0.243	0.046
CR1	2.54	-1.96	0.148	-0.079
CR2	4.54	-1.54	0.271	-0.067
PSVR	0.66	-0.07	0.146	-0.014
AIKP	4.77	0.45	0.344	0.034
AIKN	3.74	2.32	0.283	0.176
CLMP	2.31	1.07	0.371	0.154
CLMN	3.37	1.02	0.397	0.131
PUMP	1.17	0.06	0.133	0.010
PUMN	1.88	0.40	0.236	0.053
SMDP	1.66	0.44	0.301	0.069
SMDN	2.88	0.85	0.447	0.131
EFMP	1.45	0.65	0.179	0.121
EFMN	2.41	-0.15	0.265	-0.022
LCIP	2.33	2.50	1.000	1.000
LCIN	0.95	-0.37	0.307	-0.140

VARIATE: LCIN (N = 134; 62 FEMALES AND 72 MALES)

VARIATE	COVARIANCES FEMALES	COVARIANCES MALES	CORRELATIONS FEMALES	CORRELATIONS MALES
OSAT	65.82	5.51	0.521	0.043
VSAT	56.19	-17.77	0.401	-0.139
HSPC	0.34	-1.75	0.029	-0.171
HSCA	0.44	-0.49	0.058	-0.076
HSPS	0.22	1.44	0.021	0.166
ROMA	-9.25	0.09	-0.321	0.006
ROPS	6.01	-4.15	0.121	-0.074
ALG	2.77	0.35	0.309	0.052
TRIG	1.25	0.41	0.219	0.094
UNIT1	5.42	-2.68	0.215	-0.214
UNIT2	11.30	-5.12	0.230	-0.193
UNIT3	8.33	0.60	0.146	0.026
UNIT4	2.76	2.54	0.045	0.070
FINAL	3.45	-1.58	0.206	-0.136
GEFT2	0.81	-0.61	0.177	-0.192
GEFT3	0.19	-0.18	0.055	-0.078
HPT1	5.39	3.11	0.148	0.110
HPT2	13.90	-2.43	0.376	-0.089
NS1	0.81	-0.20	0.089	-0.026
NS2	3.71	0.39	0.429	0.053
DR1	-4.76	-0.19	-0.201	-0.038
DR2	2.42	-0.16	0.386	-0.030
CR1	0.84	-0.90	0.037	-0.034
CR2	6.00	-4.15	0.269	-0.170
PSVR	1.10	-0.48	0.182	-0.089
AIKP	-0.99	1.68	-0.054	0.120
AIKN	0.64	2.51	0.036	0.178
CLMP	-0.69	0.54	-0.083	0.073
CLMN	0.26	0.63	0.023	0.077
PUMP	-1.59	0.88	-0.136	0.141
PUMN	-1.52	1.41	-0.144	0.179
SMDP	-0.55	0.09	-0.074	0.013
SMDN	0.25	0.78	0.029	0.113
EFMP	0.16	0.93	0.015	0.164
EFMN	-0.67	-0.07	-0.056	-0.010
LCIP	0.95	-0.37	0.307	-0.140
LCIN	4.12	2.82	1.000	1.000

Table 9. Discriminant analysis results

Measure	Brief Description	Disc. Coeff.
QSAT	quantitative SAT score	-0.11
VSAT	verbal SAT score	0.23
HSPC	grade points in precalculus	-0.38
HSCA	grade points in calculus	-0.21
HSPS	grade points in physical science	0.08
RQMA	sem. hrs. math required in major	-0.16
RQPS	sem. hrs. phys. sci. required in major	0.56
ALG	algebra pretest score	0.47
TRIG	trigonometry pretest score	-0.34
UNIT1	unit 1 calculus exam score	-0.39
UNIT2	unit 2 calculus exam score	0.62
UNIT3	unit 3 calculus exam score	-0.22
UNIT4	unit 4 calculus exam score	0.40
FINAL	final calculus exam score	-0.19
GEFT2	group emb. fig. test section 2	-0.12
GEFT3	group emb. fig. test section 3	0.03
HPT1	hidden patterns test part 1	0.04
HPT2	hidden patterns test part 2	-0.15
NS1	nonsense syllogisms part 1	-0.12
NS2	nonsense syllogisms part 2	0.07
DR1	diagramming relationships part 1	-0.01
DR2	diagramming relationships part 2	-0.18
CR1	card rotations part 1	-0.49
CR2	card rotations part 2	0.14
PSVR	Purdue spatial visual. of rotations	0.09
AIKP	Aiken scale "positive" items	-0.02
AIKN	Aiken scale "negative" items	-0.18
CLMP	F-S Confidence scale "positive" items	0.38
CLMN	F-S Confidence scale "negative" items	-0.28
PUMP	F-S Usefulness scale "positive" items	0.80
PUMN	F-S Usefulness scale "negative" items	-0.34
SMDP	F-S Male Domain scale "positive" items	-0.27
SMDN	F-S Male Domain scale "negative" items	-0.38
EFMP	F-S Effect. Mot. scale "positive" items	-0.74
EFMN	F-S Effect. Mot. scale "negative" items	0.79
LCIP	locus of control scale "positive" items	0.56
LCIN	locus of control scale "negative" items	0.08

Above, Disc. Coeff. refers to the standardized canonical discriminant function coefficient of the measure. The value of this discriminant function at the group means was -1.117 for females, and 0.962 for males. Under the assumption of equal variance-covariance matrices (which was violated), this difference is significant at the .0001 level.

Indications from the exploratory work for model development

We close this chapter with a summary of the results from our exploratory work using principal component analysis, traditional factor analysis, and canonical correlate analysis with the sample estimates of the covariances provided by the first subsample.

Principal component analysis indicated that eleven factors could explain over 70 percent of the common variance among the 37 variates included in this study for both males and females (see Table 10 below). Inclusion of more factors in the models would, of course, explain more, but their relative contributions would be quite small. After the eleventh principal component, each succeeding principal component had an eigenvalue less than 1, with less than 3% of the common variance accounted for by each one.

Table 10. Principal component analysis results

	Females		Males	
Factor	Eigenvalue	% of variance	Eigenvalue	% of variance
1	9.92	26.8	7.04	19.0
2	3.77	10.2	3.80	10.3
3	2.70	7.3	2.94	8.0
4	2.31	6.3	2.57	6.9
5	1.98	5.4	2.17	5.9
6	1.65	4.4	2.03	5.5
7	1.47	4.0	1.66	4.5
8	1.45	3.9	1.53	4.1
9	1.29	3.5	1.35	3.7
10	1.14	3.1	1.22	3.3
11	1.11	3.0	1.19	3.2
		77.8		74.3

Traditional factor analyses (using a variety of rotations) and canonical correlate analyses were performed to aid in the choosing of specifying variates for factors. Some variates did not appear to load on any factor in a discernible pattern for either males or females. Other variates, specifically the calculus unit and final exams, were reserved for use as criterion variates. In the interests of parsimony, we concentrated on specifying nine factors for each of the models.

The specification of variates for each factor can best be described by dividing the factors into three domains: cognitive, affective, and participation/preparation.

Cognitive factors

The measures of spatial ability used in the study, CR1, CR2, and PSVR, did not consistently load heavily on the same factor for either males or females. One could interpret this as evidence that a multi-factor definition of spatial ability is most appropriate. Perhaps if we had used more and/or different measuring instruments, this might be more apparent. Logically, one might wonder if the two-dimensional tasks represented by the Card Rotations tests might involve distinctly different skills than the three-dimensional tasks represented by the PSVR. However, the evidence for two distinct spatial factors for the measures employed in this study did not seem pressing enough to justify specifying more than one spatial ability factor. It must be emphasized that we are not claiming that this is an adequate view of spatial ability in general. We are merely saying that for the three measures employed in this study, it appeared that specification of a single factor would suffice. In this study, we abbreviated this spatial ability factor as SA.

On the other hand, the Hidden Patterns test and the Group Embedded Figures Test clearly loaded on distinct factors for both males and females. We found this somewhat surprising, given the superficially similar quality of the tasks represented in these measures. Nevertheless, the evidence of a two-factor structure was strong enough to specify two different factors. HPT1 and HPT2 specified a factor we called flexibility of closure (abbreviated FC) and GEFT2 and GEFT3 specified a factor which was called field independence/ field dependence (abbreviated FI/FD).

The measures of logical reasoning, Nonsense Syllogisms and Diagramming Relationships from the Ekstrom Kit, as well as the verbal score from the Scholastic Aptitude Test, showed very modest loadings on all the factors from the exploratory analysis. This might indicate that these measures are more appropriate in a different "universe" of variates than those most closely related to calculus achievement. In an investigation of mathematics achievement and participation at levels beyond the calculus, such as abstract algebra or analysis, these variates might play a greater role in identifying factor structure. For the models developed in this study, we chose not to include these variates as specifying variates for any factor, but we did note what contributions the factors made to explaining their intercorrelations.

Affective Factors

There was strong support for a three-factor structure for the affective scales, as nearly 100% of their common variance could be explained by such a structure for both males and females. Table 11 displays the results of a factor analysis using an equimax rotation of the loading matrix of the affective measures on the three factors for males and females, respectively.

Table 11. Factor analysis of affective scales

Variate	Factor 1		Factor 2		Factor 3	
	males	females	males	females	males	females
AIKP	0.75	0.86	0.42	0.24	-0.19	0.09
AIKN	0.83	0.76	0.27	0.34	-0.02	0.13
CLMP	0.78	0.76	0.32	0.17	-0.06	0.15
CLMN	0.80	0.81	0.24	0.41	0.03	0.19
PUMP	0.18	0.50	0.77	0.63	0.05	-0.30
PUMN	0.09	0.41	0.90	0.77	0.25	-0.14
SMDP	-0.21	0.20	0.07	0.41	0.11	0.10
SMDN	0.11	-0.06	0.24	0.75	0.89	0.49
EFMP	0.60	0.66	0.43	0.50	-0.24	-0.21
EFMN	0.43	0.52	0.57	0.73	0.14	-0.05
LCIP	0.19	0.25	-0.05	0.25	0.14	0.64
LCIN	0.06	-0.01	0.17	-0.08	0.01	0.31

The Aiken scales and the Fennema-Sherman Confidence in Learning Mathematics and Effectance Motivation in Mathematics scales all loaded heavily on one factor. This agreed with similar results of a principal factor analysis that Fennema and Sherman performed with their scales with younger subjects (Fennema & Sherman, 1976). We referred to this factor as attitude toward learning mathematics (abbreviated ALM).

The Usefulness of Mathematics scales and the Mathematics as a Male Domain scales loaded onto the second and third factors in a different pattern for males and females. In order to examine this difference more closely in the confirmatory analysis with Factorial Modeling, we specified another factor called perceived usefulness of mathematics (abbreviated PUM), and a third factor which we called perceived appropriateness of mathematics for females (abbreviated PAMF). The locus of control scales developed for this study, LCIP and LCIN, showed an inconsistent pattern of loadings in all the factor analyses, including the one displayed in Table 11. Considering this, along with their low reliability in comparison with the other affective measures (see Table 6 on page 43), we decided not to use these scales as specifying variates for any of the factors.

While the three-factor structure for affective scales seemed sufficient for both males and females, we note that the exploratory canonical correlate analysis indicated that the affective factors may play a greater role for females than males. Four pairs of canonical correlates (significant at the alpha = .10 level) were found between the set of affective neasures and the set of calculus unit and final exams. Only one significant pair of canonical correlates was found for the males. In examining the correlations themselves, the measures SMDP and SMDN enjoyed higher correlations with the achievement measures for females than males. Hence the factor PAMF may have a greater part in explaining correlations among the variates for females than males.

Participation and preparation factors

Three other factors were proposed for the models for both males and females: academic experience (abbreviated AE), precalculus preparation (abbreviated PCP) and future academic plans (abbreviated FAP). The measures of high school participation in mathematics and physical sciences (HSPC, HSCA, and HSPS) were used as specifying variates for AE. The quantitative score on the Scholastic Aptitude Test (QSAT) and the algebra and trigonometry pretests (ALG and TRIG) were used as specifying variates for PCP. Finally, semester hours required in mathrmatics and physical science and engineering (RQMA and RQPS) were used as specifying variates for FAP.

The unit exams and final exam were of interest as criterion variates and thus were not considered as specifying variates for any additional factors. Since the decision was made not to specify any factors with VSAT, NS1, NS2, DR1, DR2, LCIP, or LCIN, we felt that the nine factors specified above should be sufficient for the factor models for both males and females. We summarize these nine factor specifications in Table 12 on the following page. See Tables 1-4 (pages 39-41) for an explanation of the abbreviations for the variates.

In the next chapter, we provide the results of the parameter estimations and confirmatory analysis using Factorial Modeling and the sample correlations from the second subsample.

Table 12. Specifying variates for the factors

Factor	Abbreviation	Specifying variates
academic experience	AE	HSPC, HSCA, HSPS
precalculus preparation	PCP	QSAT, ALG, TRIG
future academic plans	FAP	RQMA, RQPS
perceived appropriateness of mathematics for females	PAMF	SMDP, SMDN
perceived usefulness of mathematics	PUM	PUMP, PUMN
attitude toward learning mathematics	ALM	AIKP, AIKN, CLMP, CLMN, EFMP, EFMN
spatial ability	SA	CR1, CR2, PSVR
field independence/ field dependence	FI/FD	GEFT2, GEFT3
flexibility of closure	FC	HPT1, HPT2

CHAPTER VI

RESULTS OF THE CONFIRMATORY ANALYSIS

In this chapter we report the results of the use of Factorial Modeling for estimating the parameters of the models for males and females. Refer to Tables 1-4 on pages 39-41 and Table 12 on page 150 for explanations of the abbreviations used for variates and factors.

The models for males and females are parallel in terms of number of factors, specifying variates for the factors, and the criterion variates. The structural parameters will highlight any differences in covariance structure. The exact order of extraction used for both males and females was guided by several considerations. First, we were interested in the influence of affective and cognitive factors after controlling for previous academic experience and preparation. This was accomplished by extracting the factors AE and PCP first. Secondly, our exploratory analysis indicated that the most profound differences between males and females were in the affective domain, specifically with regards to the perceived appropriateness of mathematics for females and the perceived usefulness of mathematics (PAMF and PUM). These factors were extracted next. Future academic plans was the factor indicating future participation in mathematics, science and engineering, and this factor (FAP) was the next extracted, followed by the affective factor, attitude toward learning mathematics (ALM).

Since programs to change the cognitive variables would most likely require the most effort and cost in terms of developing instructional materials, educational policymakers might want to know the influences of these variables on mathematics achievement and participation only after all the other factors were controlled. The factors representing spatial ability, field independence/ field dependence, and flexibility of closure (SA, FI/FD, and FC) were extracted last, so that we could judge these influences.

As for a criterion variate, the most obvious choice was FINAL, the final calculus exam, since it represented the most recent measure of the students' mathematics achievement. The other calculus exams, as well as those variates not used as specifying variates for any of the factors were included in the confirmatory analysis in order to examine the influences of the factors on all variates measured in this study.

We summarize this information in Table 13 below.

Table 13. Factorial Modeling specifications for models

Order of extraction:

1) AE
2) PCP
3) PAMF
4) PUM
5) FAP
6) ALM
7) SA
8) FI/FD
9) FC

Variates not used as specifying variates:
VSAT, NS1, NS2, DR1, DR2, LCIP, LCIN, UNIT1, UNIT2, UNIT3, UNIT4.

Criterion variate: FINAL

Because of the number of variates and factors involved, a single path diagram for either model would contain so many arrows as to become too unwieldy to interpret easily. For this reason, we broke the path diagrams down into several subdiagrams. We divided the 9 factors into three groups and the 37 variates into six groups. We then prepared a path diagram for each combination of factor group and variate group, for a total of 18 subdiagrams. The breakdown of factors and variates into groups is displayed in Table 14 below:

Table 14. Factor and variate groups for path diagrams

Factor groups

1) AE, PCP, FAP
2) PAMF, PUM, ALM
3) SA, FI/FD, FC

Variate groups

1) HSPC, HSCA, HSPS, QSAT, ALG, TRIG
2) SMDP, SMDN, PUMP, PUMN, RQMA, RQPS
3) AIKP, AIKN, CLMP, CLMN, EFMP, EFMN
4) CR1, CR2, PSVR, GEFT2, GEFT3, HPT1, HPT2
5) UNIT1, UNIT2, UNIT3, UNIT4, FINAL
6) VSAT, NS1, NS2, DR1, DR2, LCIP, LCIN

For ease of comparison of males and females, the path coefficients for both sexes are displayed side by side on each of the subdiagrams. To further simplify these diagrams, we made several conventions. First, we only included arrows from factors to variates with path coefficients of absolute value at least 0.225. Put another way, we displayed an arrow from a factor to a variate only if that factor could account for at least 5% of the variance in that variate. Secondly, we deleted the disturbance factor labels for each variate. Instead, we simply included an arrow without a source pointing to each variate and labelled it with the disturbance coefficient (i.e., we did not include circled labels for the disturbance factors themselves). With these conventions made, we refer to such diagrams as reduced path diagrams. Note that the full set of structure coefficients can be found in the factor structure matrix.

At any particular stage of the factor extraction process, it is possible one or more of the specifying variates of a factor are negatively correlated with the criterion variate. The FaM algorithm could then result in that factor being positively correlated with the criterion variate, but negatively correlated with the specifying variates for that factor. Because of this possibility, we decided to reflect any factor (i.e., change the sign of all its structural coefficients) which was negatively correlated with more than half of its specifying variates. Such a procedure in no way affects the fit of the model, and provides us with factors positively correlated with as many of their specifying variates as possible, as well as indicating the "correct" sign on the covariance with the criterion variate. The factors in the model for females which were reflected were ALM, FI/FD, and FC. The factors in the model for males which were reflected were SA and FC.

On the following pages the descriptive statistics for males and females in the second subsample and the results of the FaM procedure are reported. This information is arranged in the following tables:

Table 15. means and standard deviations of variates

Table 16. correlation matrices (R in FaM description)

Table 17. structure matrices (i.e. the matrices of path coefficients from factors to variates, S)

Table 18. matrices of squared structure coefficients

Table 19. communalities and disturbance terms (h_j^2 and d_j)

Table 20. final residual correlation matrices (R_{n+1})

Table 21. factor theory correlation matrices (SS')

Table 22. matrices of factor-scoring coefficients

Following these tables, in Figures 1-18, are the reduced path diagrams for the models. Finally, indications of goodness-of-fit for the models are reported at the end of this chapter.

Table 15. Means and standard deviations of variates (2nd subsample)

DESCRIPTIVE STATISTICS FOR SECOND SUBSAMPLE

	FEMALES		MALES	
VARIATE	MEAN	ST. DEV.	MEAN	ST. DEV.
HSPC	26.34	4.70	26.18	5.29
HSCA	3.10	3.97	2.89	3.84
HSPS	14.37	5.11	15.88	5.48
QSAT	557.90	58.81	598.89	65.76
ALG	14.60	3.99	14.99	4.35
TRIG	4.29	2.22	5.18	2.58
SMDP	27.65	2.72	25.94	4.01
SMDN	27.20	3.63	25.33	4.20
PUMP	22.87	4.63	25.13	3.70
PUMN	24.69	4.29	25.28	4.50
ROMA	9.81	11.17	11.39	10.21
RQPS	21.85	26.80	35.75	33.42
AIKP	32.58	8.41	31.17	8.20
AIKN	36.83	7.27	36.97	8.05
CLMP	20.75	4.06	21.87	3.82
CLMN	22.77	4.55	23.22	4.42
EFMP	19.87	4.34	20.07	4.61
EFMN	22.43	4.92	21.79	5.13
CR1	59.42	16.86	63.56	13.91
CR2	50.94	15.40	56.68	12.70
PSVR	5.26	2.69	6.82	3.59
GEFT2	5.97	2.10	6.39	2.18
GEFT3	7.53	1.96	7.97	1.29
HPT1	107.98	16.51	114.39	18.74
HPT2	109.42	19.68	116.58	19.63
VSAT	488.71	63.69	505.56	78.83
NS1	2.18	3.77	3.81	4.85
NS2	2.82	4.25	6.24	4.17
DR1	7.95	3.33	9.49	3.45
DR2	9.91	3.60	11.03	3.16
LCIP	5.02	1.67	5.57	1.79
LCIN	5.45	1.84	5.02	1.79
UNIT1	91.60	7.31	90.14	13.36
UNIT2	65.90	22.80	71.57	21.67
UNIT3	74.52	26.33	79.39	19.04
UNIT4	64.29	27.82	67.10	24.62
FINAL	18.08	7.12	18.85	7.02

Table 16. Correlation matrices

CORRELATION MATRIX FOR FEMALES

VARIATE	HSPC	HSCA	HSPS	QSAT	ALG	TRIG	SMDP	SMDN
HSPC	1.000	0.189	0.331	0.079	0.006	0.124	0.174	0.124
HSCA	0.189	1.000	0.263	0.201	0.171	0.149	0.042	-0.023
HSPS	0.331	0.263	1.000	0.280	0.154	0.143	0.119	0.096
QSAT	0.079	0.201	0.280	1.000	0.469	0.199	0.082	0.013
ALG	0.006	0.171	0.154	0.469	1.000	0.381	-0.086	-0.071
TRIG	0.124	0.149	0.143	0.199	0.381	1.000	0.115	0.157
SMDP	0.174	0.042	0.119	0.082	-0.086	0.115	1.000	0.567
SMDN	0.124	-0.023	0.096	0.013	-0.071	0.157	0.567	1.000
PUMP	0.505	0.178	0.297	0.175	0.269	0.269	0.099	0.125
PUMN	0.307	0.159	0.207	0.328	0.181	0.356	0.284	0.309
ROMA	0.192	0.159	0.280	0.122	0.366	0.237	-0.058	-0.025
ROPS	-0.011	0.121	0.302	0.221	0.329	0.278	0.135	0.037
AIKP	0.229	0.292	0.271	0.331	0.342	0.130	0.020	0.157
AIKN	0.044	0.229	0.243	0.415	0.341	0.199	-0.035	0.056
CLMP	0.258	0.285	0.304	0.401	0.432	0.107	-0.121	-0.056
CLMN	0.054	0.290	0.253	0.461	0.376	0.101	-0.073	0.022
EFMP	0.155	0.167	0.242	0.266	0.257	0.073	0.060	0.157
EFMN	0.141	0.102	0.203	0.234	0.111	0.125	0.194	0.416
CR1	-0.200	-0.201	-0.089	0.054	0.114	0.095	-0.088	-0.102
CR2	-0.012	-0.199	-0.038	0.168	0.245	0.148	-0.002	-0.083
PSVR	0.017	0.017	0.071	0.160	0.240	0.123	-0.006	0.102
GEFT2	-0.071	-0.005	0.154	0.258	0.189	-0.015	0.010	-0.032
GEFT3	-0.132	0.029	0.069	0.227	0.236	0.076	0.026	-0.010
HPT1	-0.141	0.011	0.109	0.107	0.289	0.016	0.097	0.012
HPT2	-0.091	-0.108	0.125	0.079	0.163	0.023	0.146	0.091
VSAT	0.077	-0.017	0.050	0.387	0.093	-0.112	0.186	0.167
NS1	-0.031	0.141	0.118	0.222	0.137	0.127	0.040	-0.109
NS2	0.026	-0.015	0.320	0.204	0.022	0.060	0.019	0.066
DR1	-0.039	-0.101	0.227	0.295	0.046	-0.197	0.019	0.061
DR2	0.177	-0.070	0.327	0.249	-0.013	-0.250	0.204	0.019
LCIP	-0.266	0.020	0.068	0.029	0.013	0.113	0.082	0.173
LCIN	-0.168	-0.066	-0.163	-0.069	-0.289	0.133	-0.041	0.102
UNIT1	-0.046	0.205	-0.046	0.089	0.242	0.202	-0.122	0.151
UNIT2	0.181	0.230	0.295	0.218	0.347	0.368	0.134	0.176
UNIT3	0.223	0.173	0.055	0.095	0.355	0.321	-0.074	0.033
UNIT4	0.244	0.253	0.347	0.226	0.404	0.381	-0.061	-0.035
FINAL	0.269	0.434	0.363	0.351	0.440	0.280	0.031	0.075

CORRELATION MATRIX FOR FEMALES

VARIATE	PUMP	PUMN	ROMA	ROPS	AIKP	AIKN	CLMP	CLMN
HSPC	0.505	0.307	0.192	-0.011	0.229	0.044	0.258	0.054
HSCA	0.178	0.159	0.159	0.121	0.292	0.229	0.285	0.290
HSPS	0.297	0.207	0.280	0.302	0.271	0.243	0.304	0.253
QSAT	0.175	0.328	0.122	0.221	0.331	0.415	0.401	0.461
ALG	0.269	0.181	0.366	0.329	0.342	0.341	0.432	0.376
TRIG	0.269	0.356	0.237	0.278	0.130	0.199	0.107	0.101
SMDP	0.099	0.284	-0.058	0.135	0.020	-0.035	-0.121	-0.073
SMDN	0.125	0.309	-0.025	0.037	0.157	0.056	-0.056	0.022
PUMP	1.000	0.695	0.280	0.325	0.312	0.070	0.448	0.159
PUMN	0.695	1.000	0.177	0.352	0.361	0.279	0.333	0.260
ROMA	0.280	0.177	1.000	0.371	0.308	0.199	0.326	0.250
ROPS	0.325	0.352	0.371	1.000	0.327	0.431	0.361	0.446
AIKP	0.312	0.361	0.308	0.327	1.000	0.820	0.688	0.738
AIKN	0.070	0.279	0.199	0.431	0.820	1.000	0.617	0.828
CLMP	0.448	0.333	0.326	0.361	0.688	0.617	1.000	0.803
CLMN	0.159	0.260	0.250	0.446	0.738	0.828	0.803	1.000
EFMP	0.526	0.416	0.154	0.357	0.665	0.457	0.514	0.441
EFMN	0.474	0.585	0.095	0.254	0.627	0.482	0.432	0.434
CR1	-0.143	-0.122	-0.031	-0.068	-0.077	0.069	0.037	0.049
CR2	-0.058	-0.022	-0.052	-0.079	0.026	0.074	0.173	0.144
PSVR	0.023	-0.079	0.109	0.081	0.319	0.355	0.265	0.315
GEFT2	-0.132	0.018	-0.036	-0.159	0.121	0.194	-0.044	-0.023
GEFT3	-0.235	0.024	0.009	0.014	0.116	0.274	-0.009	0.112
HPT1	-0.137	-0.113	0.135	0.033	-0.008	0.054	0.095	0.064
HPT2	0.055	0.254	0.079	0.042	0.099	0.184	0.274	0.188
VSAT	0.049	0.117	-0.085	0.005	-0.177	-0.141	-0.003	-0.058
NS1	0.049	-0.053	-0.046	-0.039	-0.079	-0.087	-0.018	-0.079
NS2	0.177	-0.071	0.152	0.123	-0.105	-0.094	0.107	-0.027
DR1	-0.081	-0.111	0.001	-0.005	0.036	0.066	-0.054	0.026
DR2	0.039	-0.007	-0.003	-0.063	0.134	0.103	0.090	0.040
LCIP	0.142	0.142	-0.190	0.133	0.149	0.171	0.218	0.264
LCIN	0.031	-0.004	-0.032	0.038	-0.222	-0.129	-0.035	-0.046
UNIT1	0.332	0.281	0.200	0.135	0.083	0.085	0.265	0.189
UNIT2	0.397	0.331	0.292	0.331	0.214	0.256	0.249	0.270
UNIT3	0.335	0.075	0.187	0.236	0.032	0.024	0.180	0.076
UNIT4	0.342	0.131	0.179	0.308	0.238	0.228	0.320	0.278
FINAL	0.478	0.282	0.287	0.340	0.212	0.246	0.418	0.356

CORRELATION MATRIX FOR FEMALES

VARIATE	EFMP	EFMN	CR1	CR2	PSVR	GEFT2	GEFT3	HPT1
HSPC	0.155	0.141	-0.200	-0.012	0.017	-0.071	-0.132	-0.141
HSCA	0.167	0.102	-0.201	-0.199	0.017	-0.005	0.029	0.011
HSPS	0.242	0.203	-0.089	-0.038	0.071	0.154	0.069	0.109
QSAT	0.266	0.234	0.054	0.168	0.160	0.258	0.227	0.107
ALG	0.257	0.111	0.114	0.245	0.240	0.189	0.236	0.289
TRIG	0.073	0.125	0.095	0.148	0.123	-0.015	0.076	0.016
SMDP	0.060	0.194	-0.088	-0.002	-0.006	0.010	0.026	0.097
SMDN	0.157	0.416	-0.102	-0.083	0.102	-0.032	-0.010	0.012
PUMP	0.526	0.474	-0.143	-0.058	0.023	-0.132	-0.235	-0.137
PUMN	0.416	0.585	-0.122	-0.022	-0.079	0.018	0.024	-0.113
RQMA	0.154	0.095	-0.031	-0.052	0.109	-0.036	0.009	0.135
RQPS	0.357	0.254	-0.068	-0.079	0.081	-0.159	0.014	0.033
AIKP	0.665	0.627	-0.077	0.026	0.319	0.121	0.116	-0.008
AIKN	0.457	0.482	0.069	0.074	0.355	0.194	0.274	0.054
CLMP	0.514	0.432	0.037	0.173	0.265	-0.044	-0.009	0.095
CLMN	0.441	0.434	0.049	0.144	0.315	-0.023	0.112	0.064
EFMP	1.000	0.797	-0.162	-0.103	0.091	-0.063	-0.129	-0.097
EFMN	0.797	1.000	-0.180	-0.142	0.098	0.029	-0.014	-0.057
CR1	-0.162	-0.180	1.000	0.765	0.280	0.264	0.145	0.363
CR2	-0.103	-0.142	0.765	1.000	0.367	0.164	0.175	0.340
PSVR	0.091	0.098	0.280	0.367	1.000	0.113	0.201	0.218
GEFT2	-0.063	0.029	0.264	0.164	0.113	1.000	0.690	0.334
GEFT3	-0.129	-0.014	0.145	0.175	0.201	0.690	1.000	0.283
HPT1	-0.097	-0.057	0.363	0.340	0.218	0.334	0.283	1.000
HPT2	0.052	0.135	0.422	0.316	0.169	0.196	0.078	0.693
VSAT	0.110	0.199	-0.152	0.009	0.054	0.076	0.097	0.038
NS1	0.121	-0.115	-0.056	0.015	0.148	0.129	0.081	-0.061
NS2	-0.078	-0.105	0.088	0.080	0.001	0.104	0.103	0.112
DR1	0.182	0.135	0.157	0.200	0.274	0.196	-0.053	0.003
DR2	0.181	0.165	0.211	0.302	0.264	0.234	0.037	0.195
LCIP	0.428	0.296	0.161	0.138	-0.096	-0.138	-0.228	0.086
LCIN	-0.152	-0.088	0.153	-0.041	-0.231	-0.239	-0.403	-0.043
UNIT1	0.110	0.127	0.103	-0.031	0.129	-0.123	-0.138	-0.033
UNIT2	0.259	0.174	0.053	0.120	-0.022	-0.042	-0.009	0.042
UNIT3	0.192	-0.005	0.099	0.130	0.043	-0.091	-0.022	-0.047
UNIT4	0.248	0.096	0.155	0.197	0.048	0.081	0.146	0.047
FINAL	0.319	0.216	0.010	0.053	0.077	-0.050	-0.011	0.005

CORRELATION MATRIX FOR FEMALES

VARIATE	HPT2	VSAT	NS1	NS2	DR1	DR2	LCIP	LCIN
HSPC	-0.091	0.077	-0.031	0.026	-0.039	0.177	-0.266	-0.168
HSCA	-0.108	-0.017	0.141	-0.015	-0.101	-0.070	0.020	-0.066
HSPS	0.125	0.050	0.118	0.320	0.227	0.327	0.068	-0.163
QSAT	0.079	0.387	0.222	0.204	0.295	0.249	0.029	-0.069
ALG	0.163	0.093	0.137	0.022	0.046	-0.013	0.013	-0.289
TRIG	0.023	-0.112	0.127	0.060	-0.197	-0.250	0.113	0.133
SMDP	0.146	0.186	0.040	0.019	0.019	0.204	0.082	-0.041
SMDN	0.091	0.167	-0.109	0.066	0.061	0.019	0.173	0.102
PUMP	0.055	0.049	0.049	0.177	-0.081	0.039	0.142	0.031
PUMN	0.254	0.117	-0.053	-0.071	-0.111	-0.007	0.142	-0.004
ROMA	0.079	-0.085	-0.046	0.152	0.001	-0.003	-0.190	-0.032
ROPS	0.042	0.005	-0.039	0.123	-0.005	-0.063	0.133	0.038
AIKP	0.099	-0.177	-0.079	-0.105	0.036	0.134	0.149	-0.222
AIKN	0.184	-0.141	-0.087	-0.094	0.066	0.103	0.171	-0.129
CLMP	0.274	-0.003	-0.018	0.107	-0.054	0.090	0.218	-0.035
CLMN	0.188	-0.053	-0.079	-0.027	0.026	0.040	0.264	-0.046
EFMP	0.052	0.110	0.121	-0.078	0.182	0.181	0.428	-0.152
EFMN	0.135	0.199	-0.115	-0.105	0.135	0.165	0.296	-0.088
CR1	0.422	-0.152	-0.056	0.088	0.157	0.211	0.161	0.153
CR2	0.316	0.009	0.015	0.080	0.200	0.302	0.138	-0.041
PSVR	0.169	0.054	0.148	0.001	0.274	0.264	-0.096	-0.231
GEFT2	0.196	0.076	0.129	0.104	0.196	0.234	-0.138	-0.239
GEFT3	0.078	0.097	0.081	0.103	-0.053	0.037	-0.228	-0.403
HPT1	0.693	0.038	-0.061	0.112	0.003	0.195	0.086	-0.043
HPT2	1.000	0.038	-0.105	-0.070	-0.007	0.230	0.224	0.246
VSAT	0.038	1.000	0.248	0.349	0.311	0.266	-0.001	0.118
NS1	-0.105	0.248	1.000	0.312	0.107	0.064	0.284	-0.018
NS2	-0.070	0.349	0.312	1.000	0.115	0.037	0.204	0.278
DR1	-0.007	0.311	0.107	0.115	1.000	0.642	0.125	0.037
DR2	0.230	0.266	0.064	0.037	0.642	1.000	0.017	-0.188
LCIP	0.224	-0.001	0.284	0.204	0.125	0.017	1.000	0.282
LCIN	0.246	0.118	-0.018	0.278	0.037	-0.188	0.282	1.000
UNIT1	0.168	-0.010	0.006	-0.009	-0.164	-0.081	0.166	0.373
UNIT2	0.078	0.011	0.167	0.203	-0.010	0.092	0.193	0.158
UNIT3	-0.095	-0.008	0.138	0.138	-0.151	-0.167	0.129	0.158
UNIT4	-0.003	-0.002	0.162	0.239	-0.173	0.048	0.211	0.005
FINAL	-0.014	0.140	0.205	0.227	-0.058	0.038	0.149	-0.063

CORRELATION MATRIX FOR FEMALES

VARIATE	UNIT1	UNIT2	UNIT3	UNIT4	FINAL
HSPC	-0.046	0.181	0.223	0.244	0.269
HSCA	0.205	0.230	0.173	0.253	0.434
HSPS	-0.046	0.295	0.055	0.347	0.363
QSAT	0.089	0.218	0.095	0.226	0.351
ALG	0.242	0.347	0.355	0.404	0.440
TRIG	0.202	0.368	0.321	0.381	0.280
SMDP	-0.122	0.134	-0.074	-0.061	0.031
SMDN	0.151	0.176	0.033	-0.035	0.075
PUMP	0.332	0.397	0.335	0.342	0.478
PUMN	0.281	0.331	0.075	0.131	0.282
ROMA	0.200	0.292	0.187	0.179	0.287
ROPS	0.135	0.331	0.236	0.308	0.340
AIKP	0.083	0.214	0.032	0.238	0.212
AIKN	0.085	0.256	0.024	0.228	0.246
CLMP	0.265	0.249	0.180	0.320	0.418
CLMN	0.189	0.270	0.076	0.278	0.356
EFMP	0.110	0.259	0.192	0.248	0.319
EFMN	0.127	0.174	-0.005	0.096	0.216
CR1	0.103	0.053	0.099	0.155	0.010
CR2	-0.031	0.120	0.130	0.197	0.053
PSVR	0.129	-0.022	0.043	0.048	0.077
GEFT2	-0.123	-0.042	-0.091	0.081	-0.050
GEFT3	-0.138	-0.009	-0.022	0.146	-0.011
HPT1	-0.033	0.042	-0.047	0.047	0.005
HPT2	0.168	0.078	-0.095	-0.003	-0.014
VSAT	-0.010	0.011	-0.008	-0.002	0.140
NS1	0.006	0.167	0.138	0.162	0.205
NS2	-0.009	0.203	0.138	0.239	0.227
DR1	-0.164	-0.010	-0.151	-0.173	-0.058
DR2	-0.081	0.092	-0.167	0.048	0.038
LCIP	0.166	0.193	0.129	0.211	0.149
LCIN	0.373	0.158	0.158	0.005	-0.063
UNIT1	1.000	0.496	0.563	0.470	0.525
UNIT2	0.496	1.000	0.699	0.722	0.719
UNIT3	0.563	0.699	1.000	0.811	0.753
UNIT4	0.470	0.722	0.811	1.000	0.773
FINAL	0.525	0.719	0.753	0.773	1.000

CORRELATION MATRIX FOR FEMALES

VARIATE	UNIT1	UNIT2	UNIT3	UNIT4	FINAL
HSPC	-0.046	0.181	0.223	0.244	0.269
HSCA	0.205	0.230	0.173	0.253	0.434
HSPS	-0.046	0.295	0.055	0.347	0.363
QSAT	0.089	0.218	0.095	0.226	0.351
ALG	0.242	0.347	0.355	0.404	0.440
TRIG	0.202	0.368	0.321	0.381	0.280
SMDP	-0.122	0.134	-0.074	-0.061	0.031
SMDN	0.151	0.176	0.033	-0.035	0.075
PUMP	0.332	0.397	0.335	0.342	0.478
PUMN	0.281	0.331	0.075	0.131	0.282
ROMA	0.200	0.292	0.187	0.179	0.287
RQPS	0.135	0.331	0.236	0.308	0.340
AIKP	0.083	0.214	0.032	0.238	0.212
AIKN	0.085	0.256	0.024	0.228	0.246
CLMP	0.265	0.249	0.180	0.320	0.418
CLMN	0.189	0.270	0.076	0.278	0.356
EFMP	0.110	0.259	0.192	0.248	0.319
EFMN	0.127	0.174	-0.005	0.096	0.216
CR1	0.103	0.053	0.099	0.155	0.010
CR2	-0.031	0.120	0.130	0.197	0.053
PSVR	0.129	-0.022	0.043	0.048	0.077
GEFT2	-0.123	-0.042	-0.091	0.081	-0.050
GEFT3	-0.138	-0.009	-0.022	0.146	-0.011
HPT1	-0.033	0.042	-0.047	0.047	0.005
HPT2	0.168	0.078	-0.095	-0.003	-0.014
VSAT	-0.010	0.011	-0.008	-0.002	0.140
NS1	0.006	0.167	0.138	0.162	0.205
NS2	-0.009	0.203	0.138	0.239	0.227
DR1	-0.164	-0.010	-0.151	-0.173	-0.058
DR2	-0.081	0.092	-0.167	0.048	0.038
LCIP	0.166	0.193	0.129	0.211	0.149
LCIN	0.373	0.158	0.158	0.005	-0.063
UNIT1	1.000	0.496	0.563	0.470	0.525
UNIT2	0.496	1.000	0.699	0.722	0.719
UNIT3	0.563	0.699	1.000	0.811	0.753
UNIT4	0.470	0.722	0.811	1.000	0.773
FINAL	0.525	0.719	0.753	0.773	1.000

CORRELATION MATRIX FOR MALES

VARIATE	PUMP	PUMN	ROMA	ROPS	AIKP	AIKN	CLMP	CLMN
HSPC	0.294	0.167	0.249	0.132	0.306	0.258	0.354	0.234
HSCA	0.282	0.340	0.296	0.273	0.208	0.184	0.224	0.264
HSPS	0.210	0.138	0.061	0.284	0.280	0.260	0.118	0.148
QSAT	0.372	0.405	0.222	0.394	0.309	0.317	0.264	0.385
ALG	0.363	0.286	0.321	0.360	0.358	0.352	0.280	0.401
TRIG	0.244	0.260	0.371	0.236	0.429	0.463	0.400	0.451
SMDP	0.036	-0.059	-0.075	0.004	-0.132	-0.149	-0.167	-0.105
SMDN	0.224	0.305	0.187	-0.012	0.066	0.063	0.105	0.093
PUMP	1.000	0.804	0.390	0.481	0.603	0.644	0.641	0.619
PUMN	0.804	1.000	0.395	0.450	0.502	0.581	0.545	0.566
ROMA	0.390	0.395	1.000	0.371	0.386	0.377	0.440	0.441
ROPS	0.481	0.450	0.371	1.000	0.168	0.226	0.186	0.256
AIKP	0.603	0.502	0.386	0.168	1.000	0.863	0.794	0.795
AIKN	0.644	0.581	0.377	0.226	0.863	1.000	0.792	0.892
CLMP	0.641	0.545	0.440	0.186	0.794	0.792	1.000	0.805
CLMN	0.619	0.566	0.441	0.256	0.795	0.892	0.805	1.000
EFMP	0.638	0.595	0.241	0.164	0.710	0.644	0.651	0.570
EFMN	0.518	0.614	0.178	0.154	0.669	0.645	0.551	0.593
CR1	0.081	0.200	-0.074	0.158	0.029	0.040	0.083	0.098
CR2	0.212	0.245	0.001	0.229	0.148	0.135	0.185	0.167
PSVR	0.023	0.142	0.097	0.076	0.082	0.139	0.146	0.181
GEFT2	0.095	0.123	0.140	0.119	-0.140	-0.025	0.133	0.021
GEFT3	0.058	0.100	0.197	0.240	0.048	0.102	0.161	0.153
HPT1	0.130	0.135	-0.093	0.022	0.022	-0.020	0.125	-0.072
HPT2	0.007	-0.042	-0.110	-0.035	-0.037	-0.033	0.040	-0.081
VSAT	-0.036	-0.087	-0.070	0.023	-0.086	-0.071	-0.157	-0.209
NS1	0.119	0.280	0.020	-0.034	0.086	0.122	0.077	0.097
NS2	-0.109	0.022	-0.049	-0.141	-0.070	-0.118	0.059	-0.071
DP1	0.189	0.243	0.142	0.028	0.103	0.118	0.086	0.051
DP2	0.282	0.348	0.148	0.167	0.194	0.189	0.230	0.152
LCIP	0.227	0.294	0.063	0.015	0.360	0.330	0.391	0.316
LCIN	-0.134	0.048	0.104	0.013	-0.075	-0.105	0.056	0.081
UNIT1	0.296	0.233	0.254	0.348	0.121	0.181	0.197	0.219
UNIT2	0.389	0.314	0.252	0.496	0.187	0.211	0.150	0.237
UNIT3	0.277	0.177	0.063	0.334	0.259	0.331	0.210	0.298
UNIT4	0.382	0.280	0.048	0.459	0.206	0.297	0.158	0.299
FINAL	0.480	0.433	0.203	0.466	0.370	0.413	0.220	0.423

CORRELATION MATRIX FOR MALES

VARIATE	EFMP	EFMN	CR1	CR2	PSVR	GEFT2	GEFT3	HPT1
HSPC	0.404	0.192	-0.005	0.195	-0.043	0.071	0.007	-0.016
HSCA	0.185	0.085	0.202	0.212	-0.025	0.110	0.109	0.167
HSPS	0.231	0.169	0.141	0.183	0.095	0.023	0.088	0.159
QSAT	0.171	0.047	0.190	0.233	0.257	0.229	0.342	-0.035
ALG	0.252	0.059	0.091	0.135	0.066	0.104	0.153	-0.073
TRIG	0.382	0.209	0.014	0.161	0.142	0.123	0.093	0.128
SMDP	0.073	0.034	-0.050	-0.058	-0.254	-0.183	-0.124	-0.063
SMDN	0.374	0.377	0.054	0.086	-0.033	-0.001	0.008	0.085
PUMP	0.638	0.518	0.081	0.212	0.023	0.095	0.058	0.130
PUMN	0.595	0.614	0.200	0.245	0.142	0.123	0.100	0.135
RQMA	0.241	0.178	-0.074	0.001	0.097	0.140	0.197	-0.093
ROPS	0.164	0.154	0.158	0.229	0.076	0.119	0.240	0.022
AIKP	0.710	0.669	0.029	0.148	0.082	-0.140	0.048	0.022
AIKN	0.644	0.645	0.040	0.135	0.139	-0.025	0.102	-0.020
CLMP	0.651	0.551	0.083	0.185	0.146	0.133	0.161	0.125
CLMN	0.570	0.593	0.098	0.167	0.181	0.021	0.153	-0.072
EFMP	1.000	0.811	0.085	0.230	-0.077	0.019	-0.004	0.145
EFMN	0.811	1.000	0.122	0.093	-0.082	-0.113	-0.058	0.128
CR1	0.085	0.122	1.000	0.767	0.186	0.403	0.293	0.334
CR2	0.230	0.093	0.767	1.000	0.153	0.469	0.396	0.402
PSVR	-0.077	-0.082	0.186	0.153	1.000	0.399	0.346	0.113
GEFT2	0.019	-0.113	0.403	0.469	0.399	1.000	0.595	0.336
GEFT3	-0.004	-0.058	0.293	0.396	0.346	0.595	1.000	0.266
HPT1	0.145	0.128	0.334	0.402	0.113	0.336	0.266	1.000
HPT2	0.049	-0.007	0.204	0.287	0.028	0.332	0.282	0.714
VSAT	-0.101	-0.252	-0.034	0.029	0.010	0.079	0.131	-0.026
NS1	0.070	0.130	-0.039	-0.075	0.090	-0.106	0.052	-0.090
NS2	0.019	-0.101	0.200	0.155	0.019	0.194	0.231	0.089
DR1	0.084	-0.096	0.195	0.124	0.250	0.243	0.223	0.001
DR2	0.176	0.114	0.223	0.125	0.197	0.231	0.157	0.171
LCIP	0.379	0.272	0.267	0.340	0.213	0.077	-0.165	0.060
LCIN	-0.126	-0.003	0.332	0.193	0.217	0.253	0.141	0.172
UNIT1	0.228	0.230	0.105	0.074	-0.163	0.019	0.099	0.028
UNIT2	0.173	0.189	0.094	0.170	-0.073	0.110	0.132	0.023
UNIT3	0.199	0.286	0.163	0.184	-0.040	0.020	0.127	0.094
UNIT4	0.241	0.267	0.082	0.149	-0.098	-0.017	0.118	0.098
FINAL	0.351	0.307	0.099	0.201	-0.061	0.008	0.098	-0.040

CORRELATION MATRIX FOR MALES

VARIATE	HPT2	VSAT	NS1	NS2	DR1	DR2	LCIP	LCIN
HSPC	-0.026	0.047	0.074	0.073	-0.013	-0.005	0.223	-0.040
HSCA	0.050	-0.147	-0.035	0.009	0.002	0.136	-0.060	0.123
HSPS	0.136	0.194	0.054	-0.129	0.192	0.115	-0.140	0.030
QSAT	-0.010	0.337	0.303	0.123	0.460	0.357	0.157	0.123
ALG	0.016	0.112	0.175	0.105	0.324	0.245	0.074	0.099
TRIG	0.044	-0.055	0.086	0.152	0.154	0.228	0.327	-0.087
SMDP	-0.098	0.057	-0.188	-0.033	-0.093	-0.123	0.016	-0.189
SMDN	-0.031	-0.076	0.042	0.068	0.144	0.075	0.150	-0.012
PUMP	0.007	-0.036	0.119	-0.109	0.189	0.282	0.227	-0.134
PUMN	-0.042	-0.087	0.280	0.022	0.243	0.348	0.294	0.048
ROMA	-0.110	-0.070	0.020	-0.049	0.142	0.148	0.063	0.104
RQPS	-0.035	0.023	-0.034	-0.141	0.028	0.167	0.015	0.013
AIKP	-0.037	-0.086	0.086	-0.070	0.103	0.194	0.360	-0.075
AIKN	-0.033	-0.071	0.122	-0.118	0.118	0.189	0.330	-0.105
CLMP	0.040	-0.157	0.077	0.059	0.086	0.230	0.391	0.056
CLMN	-0.081	-0.209	0.097	-0.071	0.051	0.152	0.316	0.081
EFMP	0.049	-0.101	0.070	0.019	0.084	0.176	0.379	-0.126
EFMN	-0.007	-0.252	0.130	-0.101	-0.096	0.114	0.272	-0.003
CR1	0.204	-0.034	-0.039	0.200	0.195	0.223	0.267	0.332
CR2	0.287	0.029	-0.075	0.155	0.124	0.125	0.340	0.193
PSVR	0.028	0.010	0.090	0.019	0.250	0.197	0.213	0.217
GEFT2	0.332	0.079	-0.106	0.194	0.243	0.231	0.077	0.253
GEFT3	0.282	0.131	0.052	0.231	0.223	0.157	-0.165	0.141
HPT1	0.714	-0.026	-0.090	0.089	0.001	0.171	0.060	0.172
HPT2	1.000	0.128	-0.170	0.162	-0.048	0.047	0.008	0.086
VSAT	0.128	1.000	0.210	0.075	0.371	0.261	-0.191	-0.225
NS1	-0.170	0.210	1.000	0.379	0.259	0.390	0.163	-0.110
NS2	0.162	0.075	0.379	1.000	0.313	0.326	0.261	-0.108
DR1	-0.048	0.371	0.259	0.313	1.000	0.618	0.093	-0.191
DR2	0.047	0.261	0.390	0.326	0.618	1.000	0.187	-0.075
LCIP	0.008	-0.191	0.163	0.261	0.093	0.187	1.000	-0.004
LCIN	0.086	-0.225	-0.110	-0.108	-0.191	-0.075	-0.004	1.000
UNIT1	0.095	0.116	0.156	0.173	0.026	0.207	-0.015	0.056
UNIT2	0.047	0.080	0.023	-0.076	0.080	0.346	-0.086	-0.057
UNIT3	0.060	0.075	-0.005	-0.013	-0.047	0.254	0.036	-0.047
UNIT4	0.051	0.109	0.098	-0.137	-0.030	0.217	-0.009	-0.123
FINAL	0.023	0.092	0.079	-0.041	0.128	0.317	0.095	-0.051

CORRELATION MATRIX FOR MALES

VARIATE	UNIT1	UNIT2	UNIT3	UNIT4	FINAL
HSPC	0.078	0.145	-0.018	0.142	0.037
HSCA	0.213	0.226	0.172	0.300	0.353
HSPS	0.385	0.297	0.294	0.342	0.321
QSAT	0.217	0.296	0.107	0.328	0.454
ALG	0.250	0.357	0.213	0.261	0.507
TRIG	0.174	0.193	0.108	0.175	0.393
SMDP	-0.024	-0.070	-0.005	0.078	0.063
SMDN	0.059	0.055	0.023	0.052	0.061
PUMP	0.296	0.389	0.277	0.382	0.480
PUMN	0.233	0.314	0.177	0.280	0.433
ROMA	0.254	0.252	0.063	0.048	0.203
ROPS	0.348	0.496	0.334	0.459	0.466
AIKP	0.121	0.187	0.259	0.206	0.370
AIKN	0.181	0.211	0.331	0.297	0.413
CLMP	0.197	0.150	0.210	0.158	0.220
CLMN	0.219	0.237	0.298	0.299	0.423
EFMP	0.228	0.173	0.199	0.241	0.351
EFMN	0.230	0.189	0.286	0.267	0.307
CR1	0.105	0.094	0.163	0.082	0.099
CR2	0.074	0.170	0.184	0.149	0.201
PSVR	-0.163	-0.073	-0.040	-0.098	-0.061
GEFT2	0.019	0.110	0.020	-0.017	0.008
GEFT3	0.099	0.132	0.127	0.118	0.098
HPT1	0.028	0.023	0.094	0.098	-0.040
HPT2	0.095	0.047	0.060	0.051	0.023
VSAT	0.116	0.080	0.075	0.109	0.092
NS1	0.156	0.023	-0.005	0.098	0.079
NS2	0.173	-0.076	-0.013	-0.137	-0.041
DR1	0.026	0.080	-0.047	-0.030	0.128
DR2	0.207	0.346	0.254	0.217	0.317
LCIP	-0.015	-0.086	0.036	-0.009	0.095
LCIN	0.056	-0.057	-0.047	-0.123	-0.051
UNIT1	1.000	0.573	0.668	0.556	0.571
UNIT2	0.573	1.000	0.663	0.655	0.686
UNIT3	0.668	0.663	1.000	0.701	0.667
UNIT4	0.556	0.655	0.701	1.000	0.692
FINAL	0.571	0.686	0.667	0.692	1.000

Table 17. Structure matrices

FACTOR STRUCTURE MATRIX FOR FEMALES

VARIATE	AE	PCP	PAMF	PUM	FAP	ALM	SA	FI/FD	FC
HSPC	0.617	-0.097	0.009	0.297	-0.176	-0.003	0.021	0.063	0.085
HSCA	0.759	0.022	-0.033	-0.158	-0.025	-0.019	-0.086	0.072	0.021
HSPS	0.741	0.045	0.033	-0.031	0.160	0.025	0.087	-0.133	-0.088
QSAT	0.275	0.663	-0.057	-0.067	-0.070	-0.084	-0.018	-0.065	0.044
ALG	0.173	0.886	-0.004	-0.001	0.021	0.012	-0.006	-0.014	-0.071
TRIG	0.196	0.585	0.075	0.081	0.040	0.075	0.033	0.103	0.089
SMDP	0.142	-0.026	-0.277	0.105	0.054	-0.141	-0.022	-0.011	-0.157
SMDN	0.076	-0.010	0.633	0.085	0.043	-0.114	-0.017	-0.009	-0.127
PUMP	0.420	0.208	0.068	0.877	-0.009	0.022	0.002	0.013	0.013
PUMN	0.297	0.271	0.101	0.641	0.068	-0.169	-0.018	-0.099	-0.100
RQMA	0.291	0.274	0.035	0.105	0.384	0.010	0.008	0.003	-0.076
RQPS	0.208	0.324	-0.079	0.211	0.880	-0.002	-0.002	-0.001	0.015
AIKP	0.376	0.280	0.177	0.109	0.177	-0.773	0.068	0.077	-0.001
AIKN	0.261	0.365	0.106	-0.114	0.311	-0.632	0.126	-0.007	-0.016
CLMP	0.397	0.350	0.063	0.228	0.146	-0.239	0.160	0.145	-0.142
CLMN	0.304	0.361	0.104	-0.045	0.309	-0.367	0.138	0.156	-0.057
EFMP	0.264	0.214	0.135	0.413	0.157	-0.545	-0.049	0.140	-0.016
EFMN	0.204	0.143	0.310	0.414	0.095	-0.614	-0.061	0.017	-0.105
CR1	-0.227	0.186	-0.049	-0.100	-0.067	0.074	0.914	-0.042	-0.017
CR2	-0.135	0.304	-0.104	-0.067	-0.168	0.048	0.819	0.075	0.034
PSVR	0.049	0.238	0.124	-0.081	0.029	-0.195	0.360	0.028	-0.025
GEFT2	0.045	0.199	-0.047	-0.203	-0.220	-0.227	0.183	-0.863	-0.017
GEFT3	0.003	0.259	-0.039	-0.305	-0.015	-0.161	0.090	-0.720	0.046
HPT1	0.008	0.226	-0.080	-0.212	0.016	0.048	0.320	-0.220	-0.763
HPT2	-0.034	0.150	-0.035	0.073	-0.009	-0.055	0.398	-0.088	-0.846
VSAT	0.041	0.158	0.019	0.006	-0.086	0.160	-0.154	-0.112	-0.066
NS1	0.125	0.177	-0.162	-0.047	-0.156	0.124	-0.089	-0.085	0.131
NS2	0.153	0.068	0.065	0.079	0.077	0.297	0.112	-0.197	0.077
DR1	0.037	0.067	0.053	-0.138	-0.004	-0.091	0.191	-0.043	0.117
DR2	0.178	-0.044	-0.162	-0.021	-0.106	-0.208	0.321	-0.074	-0.106
LCIP	-0.050	0.069	0.122	0.163	0.056	-0.096	0.174	0.207	-0.163
LCIN	-0.174	-0.118	0.151	0.132	0.107	0.265	0.096	0.189	-0.188
UNIT1	0.078	0.230	0.293	0.264	0.028	0.183	0.063	0.088	-0.077
UNIT2	0.334	0.329	0.089	0.208	0.141	0.076	0.108	0.051	0.010
UNIT3	0.203	0.308	0.113	0.174	0.074	0.250	0.105	0.064	0.172
UNIT4	0.394	0.355	0.030	0.093	0.089	0.085	0.199	-0.039	0.137
FINAL	0.514	0.360	0.077	0.192	0.089	0.181	0.071	0.055	0.081

FACTOR STRUCTURE MATRIX FOR MALES

VARIATE	AE	PCP	PAMF	PUM	FAP	ALM	SA	FI/FD	FC
HSPC	0.252	0.145	0.085	0.122	-0.128	0.035	0.064	0.026	0.051
HSCA	0.812	-0.018	0.117	0.048	-0.098	-0.137	0.019	0.028	0.010
HSPS	0.764	0.003	-0.138	-0.066	0.123	0.147	-0.028	-0.034	-0.017
QSAT	0.413	0.613	-0.102	0.097	0.112	-0.102	-0.104	0.077	0.138
ALG	0.344	0.812	-0.007	-0.031	0.012	-0.039	0.099	-0.042	0.037
TRIG	0.304	0.638	0.117	-0.060	-0.136	0.160	-0.026	-0.025	-0.197
SMDP	-0.088	0.005	0.949	-0.097	0.084	-0.027	0.060	-0.022	0.031
SMDN	-0.073	0.105	0.750	0.209	-0.180	0.058	-0.129	0.048	-0.067
PUMP	0.329	0.306	0.126	0.837	0.014	-0.021	0.070	0.010	-0.004
PUMN	0.315	0.291	0.081	0.834	-0.017	0.024	-0.083	-0.012	0.005
RCMA	0.246	0.312	0.019	0.260	-0.527	-0.096	0.023	0.120	0.148
RQPS	0.355	0.298	0.020	0.312	0.582	-0.081	0.019	0.101	0.124
AIKP	0.323	0.356	-0.063	0.422	-0.251	0.543	0.006	-0.052	-0.035
AIKN	0.292	0.387	-0.081	0.496	-0.189	0.538	-0.032	0.023	0.053
CLMP	0.240	0.321	-0.082	0.517	-0.272	0.228	-0.063	0.092	-0.060
CLMN	0.276	0.448	-0.040	0.450	-0.208	0.471	-0.092	0.034	0.115
EFMP	0.286	0.234	0.207	0.520	-0.136	0.464	0.056	0.073	-0.110
EFMN	0.169	0.056	0.175	0.566	-0.075	0.700	0.009	0.047	-0.116
CR1	0.215	0.033	0.000	0.067	0.176	0.008	-0.555	0.110	-0.131
CR2	0.260	0.115	0.005	0.129	0.169	-0.031	-0.438	0.255	-0.182
PSVR	0.038	0.191	-0.212	0.036	-0.020	-0.073	-0.866	-0.077	0.077
GEFT2	0.090	0.167	-0.140	0.052	-0.022	-0.303	-0.451	0.627	-0.042
GEFT3	0.123	0.215	-0.090	-0.021	0.050	-0.094	-0.367	0.819	0.028
HPT1	0.202	-0.106	0.005	0.118	0.060	-0.102	-0.237	0.240	-0.886
HPT2	0.112	-0.033	-0.075	-0.040	0.045	-0.062	-0.102	0.318	-0.533
VSAT	0.023	0.178	0.011	-0.145	0.083	-0.198	0.043	0.076	0.059
NS1	0.014	0.262	-0.140	0.149	-0.074	-0.024	0.028	-0.097	0.032
NS2	-0.066	0.211	-0.016	-0.107	-0.086	-0.186	-0.073	0.163	-0.060
DR1	0.114	0.394	-0.026	0.074	-0.127	-0.246	-0.194	0.026	0.054
DR2	0.156	0.313	-0.067	0.209	-0.012	-0.129	-0.150	0.023	-0.118
LCIP	-0.107	0.302	0.043	0.236	-0.054	0.156	-0.281	-0.264	-0.103
LCIN	0.096	0.027	-0.142	-0.089	-0.079	-0.063	-0.293	0.039	-0.106
UNIT1	0.372	0.122	0.032	0.128	0.062	0.024	0.176	0.104	0.056
UNIT2	0.333	0.247	-0.013	0.209	0.202	-0.003	0.134	0.114	0.063
UNIT3	0.285	0.070	0.028	0.138	0.218	0.256	0.011	0.116	-0.017
UNIT4	0.408	0.161	0.110	0.172	0.328	0.157	0.130	0.096	-0.019
FINAL	0.423	0.440	0.091	0.216	0.192	0.163	0.138	0.024	0.096

Table 18. Matrices of squared structure coefficients

SQUARED STRUCTURE COEFFICIENTS FOR FEMALES

VARIATE	AE	PCP	PAMF	PUM	FAP	ALM	SA	FI/FD	FC
HSPC	0.380	0.009	0.000	0.088	0.031	0.000	0.000	0.004	0.007
HSCA	0.576	0.001	0.001	0.025	0.001	0.000	0.007	0.005	0.000
HSPS	0.548	0.002	0.001	0.001	0.026	0.001	0.008	0.018	0.008
QSAT	0.075	0.439	0.003	0.004	0.005	0.007	0.000	0.004	0.002
ALG	0.030	0.785	0.000	0.000	0.000	0.000	0.000	0.000	0.005
TRIG	0.038	0.342	0.006	0.006	0.002	0.006	0.001	0.011	0.008
SMDP	0.020	0.001	0.077	0.011	0.003	0.020	0.000	0.000	0.025
SMDN	0.006	0.000	0.401	0.007	0.002	0.013	0.000	0.000	0.016
PUMP	0.176	0.043	0.005	0.769	0.000	0.000	0.000	0.000	0.000
PUMN	0.088	0.073	0.010	0.411	0.005	0.028	0.000	0.010	0.010
RQMA	0.085	0.075	0.001	0.011	0.147	0.000	0.000	0.000	0.006
RQPS	0.043	0.105	0.006	0.045	0.774	0.000	0.000	0.000	0.000
ATKP	0.141	0.078	0.031	0.012	0.031	0.597	0.005	0.006	0.000
ATKN	0.068	0.133	0.011	0.013	0.097	0.399	0.016	0.000	0.000
CLMP	0.158	0.122	0.004	0.052	0.021	0.057	0.025	0.021	0.020
CLMN	0.092	0.130	0.011	0.002	0.096	0.134	0.019	0.024	0.003
EFMP	0.070	0.046	0.018	0.171	0.025	0.297	0.002	0.020	0.000
EFMN	0.042	0.020	0.096	0.171	0.009	0.377	0.004	0.000	0.011
CR1	0.051	0.034	0.002	0.010	0.005	0.005	0.835	0.002	0.000
CR2	0.018	0.092	0.011	0.005	0.028	0.002	0.670	0.006	0.001
PSVR	0.002	0.057	0.015	0.007	0.001	0.038	0.129	0.001	0.001
GEFT2	0.002	0.040	0.002	0.041	0.048	0.052	0.033	0.745	0.000
GEFT3	0.000	0.067	0.001	0.093	0.000	0.026	0.008	0.519	0.002
HPT1	0.000	0.051	0.006	0.045	0.000	0.002	0.102	0.049	0.583
HPT2	0.001	0.022	0.001	0.005	0.000	0.003	0.158	0.008	0.715
VSAT	0.002	0.025	0.000	0.000	0.007	0.026	0.024	0.012	0.004
NS1	0.016	0.031	0.026	0.002	0.024	0.015	0.008	0.007	0.017
NS2	0.023	0.005	0.004	0.006	0.006	0.088	0.013	0.039	0.006
DR1	0.001	0.004	0.003	0.019	0.000	0.008	0.036	0.002	0.014
DR2	0.032	0.002	0.026	0.000	0.011	0.043	0.103	0.005	0.011
LCIP	0.002	0.005	0.015	0.027	0.003	0.009	0.030	0.043	0.026
LCIN	0.030	0.014	0.023	0.018	0.012	0.070	0.009	0.036	0.035
UNIT1	0.006	0.053	0.086	0.069	0.001	0.034	0.004	0.008	0.006
UNIT2	0.112	0.108	0.008	0.043	0.020	0.006	0.012	0.003	0.000
UNIT3	0.041	0.095	0.013	0.030	0.005	0.062	0.011	0.004	0.029
UNIT4	0.155	0.126	0.001	0.009	0.008	0.007	0.040	0.002	0.019
FINAL	0.264	0.129	0.006	0.037	0.008	0.033	0.005	0.003	0.006

SQUARED STRUCTURE COEFFICIENTS FOR MALES

VARIATE	AE	PCP	PAMF	PUM	FAP	ALM	SA	FI/FD	FC
HSPC	0.063	0.021	0.007	0.015	0.017	0.001	0.004	0.001	0.003
HSCA	0.660	0.000	0.014	0.002	0.010	0.019	0.000	0.001	0.000
HSPS	0.583	0.000	0.019	0.004	0.015	0.022	0.001	0.001	0.000
OSAT	0.170	0.376	0.010	0.009	0.013	0.010	0.011	0.006	0.019
ALG	0.119	0.659	0.000	0.001	0.000	0.001	0.010	0.002	0.001
TRIG	0.093	0.407	0.014	0.004	0.018	0.026	0.001	0.001	0.039
SMDP	0.008	0.000	0.901	0.009	0.007	0.001	0.004	0.000	0.001
SMDN	0.005	0.011	0.562	0.044	0.032	0.003	0.017	0.002	0.004
PUMP	0.108	0.094	0.016	0.700	0.000	0.000	0.005	0.000	0.000
PUMN	0.099	0.085	0.007	0.695	0.000	0.001	0.007	0.000	0.000
ROMA	0.061	0.097	0.000	0.068	0.278	0.009	0.001	0.014	0.022
ROPS	0.126	0.089	0.000	0.098	0.339	0.007	0.000	0.010	0.015
AIKP	0.104	0.127	0.004	0.178	0.063	0.295	0.000	0.003	0.001
AIKN	0.085	0.149	0.007	0.246	0.036	0.289	0.001	0.001	0.003
CLMP	0.058	0.103	0.007	0.267	0.074	0.052	0.004	0.008	0.004
CLMN	0.076	0.200	0.002	0.203	0.043	0.222	0.008	0.001	0.013
EFMP	0.082	0.055	0.043	0.270	0.018	0.216	0.003	0.005	0.012
EFMN	0.029	0.003	0.031	0.320	0.006	0.490	0.000	0.002	0.013
CR1	0.046	0.001	0.000	0.005	0.031	0.000	0.309	0.012	0.017
CR2	0.068	0.013	0.000	0.017	0.029	0.001	0.192	0.065	0.033
PSVR	0.001	0.037	0.045	0.001	0.000	0.005	0.749	0.006	0.006
GEFT2	0.008	0.028	0.019	0.003	0.000	0.092	0.203	0.394	0.002
GEFT3	0.015	0.046	0.008	0.000	0.002	0.009	0.135	0.670	0.001
HPT1	0.041	0.011	0.000	0.014	0.004	0.011	0.056	0.057	0.785
HPT2	0.012	0.001	0.006	0.002	0.002	0.004	0.010	0.101	0.285
VSAT	0.001	0.032	0.000	0.021	0.007	0.039	0.002	0.006	0.003
NS1	0.000	0.069	0.019	0.022	0.006	0.001	0.001	0.009	0.001
NS2	0.004	0.044	0.000	0.011	0.007	0.035	0.005	0.026	0.004
DR1	0.013	0.156	0.001	0.005	0.016	0.060	0.038	0.001	0.003
DR2	0.024	0.098	0.004	0.044	0.000	0.017	0.022	0.001	0.014
LCIP	0.012	0.091	0.002	0.056	0.003	0.024	0.079	0.070	0.011
LCIN	0.009	0.001	0.020	0.008	0.006	0.004	0.086	0.001	0.011
UNIT1	0.139	0.015	0.001	0.016	0.004	0.001	0.031	0.011	0.003
UNIT2	0.111	0.061	0.000	0.044	0.041	0.000	0.018	0.013	0.004
UNIT3	0.081	0.005	0.001	0.019	0.048	0.066	0.000	0.013	0.000
UNIT4	0.167	0.026	0.012	0.030	0.107	0.025	0.017	0.009	0.000
FINAL	0.179	0.193	0.008	0.047	0.037	0.026	0.019	0.001	0.009

Table 19. Communalities and disturbance terms

COMMUNALITIES AND DISTURBANCE TERMS FOR FEMALES

VARIATE	COMMUNALITY	DISTURBANCE
HSPC	0.520	0.693
HSCA	0.617	0.619
HSPS	0.612	0.623
QSAT	0.541	0.678
ALG	0.820	0.424
TRIG	0.419	0.762
SMDP	0.156	0.918
SMDN	0.445	0.745
PUMP	0.994	0.079
PUMN	0.636	0.603
RQMA	0.325	0.822
RQPS	0.973	0.163
AIKP	0.902	0.314
AIKN	0.738	0.512
CLMP	0.481	0.720
CLMN	0.512	0.699
EFMP	0.648	0.593
EFMN	0.730	0.519
CR1	0.945	0.235
CR2	0.833	0.408
PSVR	0.251	0.866
GEFT2	0.963	0.191
GEFT3	0.716	0.533
HPT1	0.838	0.402
HPT2	0.914	0.292
VSAT	0.101	0.948
NS1	0.147	0.923
NS2	0.190	0.900
DR1	0.088	0.955
DR2	0.235	0.875
LCIP	0.161	0.916
LCIN	0.246	0.868
UNIT1	0.266	0.857
UNIT2	0.311	0.830
UNIT3	0.292	0.842
UNIT4	0.366	0.796
FINAL	0.492	0.713

COMMUNALITIES AND DISTURBANCE TERMS FOR MALES

VARIATE	COMMUNALITY	DISTURBANCE
HSPC	0.132	0.932
HSCA	0.706	0.542
HSPS	0.645	0.596
QSAT	0.625	0.612
ALG	0.793	0.454
TRIG	0.601	0.631
SMDP	0.931	0.262
SMDN	0.681	0.564
PUMP	0.924	0.276
PUMN	0.893	0.326
RQMA	0.549	0.671
ROPS	0.684	0.562
AIKP	0.775	0.475
AIKN	0.816	0.428
CLMP	0.577	0.651
CLMN	0.769	0.481
EFMP	0.704	0.544
EFMN	0.893	0.326
CR1	0.420	0.761
CR2	0.417	0.763
PSVR	0.851	0.386
GEFT2	0.749	0.501
GEFT3	0.887	0.336
HPT1	0.978	0.147
HPT2	0.423	0.760
VSAT	0.110	0.943
NS1	0.128	0.934
NS2	0.138	0.929
DR1	0.292	0.841
DR2	0.225	0.881
LCIP	0.347	0.808
LCIN	0.147	0.924
UNIT1	0.220	0.883
UNIT2	0.292	0.842
UNIT3	0.233	0.876
UNIT4	0.393	0.779
FINAL	0.520	0.693

Table 20. Final residual correlation matrices

FINAL RESIDUAL MATRIX FOR FEMALES

VARIATE	HSPC	HSCA	HSPS	QSAT	ALG	TRIG	SMDP	SMDN
HSPC	0.480	-0.239	-0.071	-0.018	-0.003	0.027	0.079	0.064
HSCA	-0.239	0.383	-0.281	-0.036	0.022	-0.002	-0.056	-0.046
HSPS	-0.071	-0.281	0.388	0.057	-0.024	-0.018	0.009	0.007
QSAT	-0.018	-0.036	0.057	0.459	-0.161	-0.220	0.049	0.039
ALG	-0.003	0.022	-0.024	-0.161	0.180	-0.164	-0.100	-0.081
TRIG	0.027	-0.002	-0.018	-0.220	-0.164	0.581	0.139	0.113
SMDP	0.079	-0.056	0.009	0.049	-0.100	0.139	0.844	0.684
SMDN	0.064	-0.046	0.007	0.039	-0.081	0.113	0.684	0.555
PUMP	0.002	-0.005	0.005	-0.014	0.015	-0.014	-0.022	-0.018
PUMN	-0.014	0.038	-0.035	0.104	-0.117	0.109	0.166	0.134
RQMA	0.082	-0.039	-0.014	-0.099	0.060	-0.002	-0.124	-0.101
RQPS	-0.016	0.008	0.003	0.020	-0.012	0.000	0.025	0.020
AIKP	0.013	0.014	-0.027	0.013	0.037	-0.089	-0.104	-0.084
AIKN	0.003	0.015	-0.021	0.071	-0.026	-0.032	-0.126	-0.103
CLMP	0.004	0.019	-0.026	0.087	0.047	-0.194	-0.233	-0.189
CLMN	-0.041	0.050	-0.030	0.147	0.001	-0.174	-0.145	-0.118
EFMP	-0.091	0.010	0.055	0.062	0.026	-0.124	-0.064	-0.052
EFMN	-0.072	0.006	0.046	0.089	-0.051	-0.003	0.102	0.083
CR1	-0.039	0.031	-0.008	-0.001	-0.007	0.015	-0.024	-0.019
CR2	0.068	-0.056	0.017	0.003	0.010	-0.025	0.042	0.034
PSVR	0.030	-0.008	-0.013	-0.015	0.023	-0.028	0.011	0.009
GEFT2	-0.007	-0.010	0.016	0.011	-0.001	-0.011	-0.012	-0.009
GEFT3	0.019	0.026	-0.045	-0.030	0.002	0.031	0.032	0.026
HPT1	0.014	0.024	-0.040	-0.034	0.030	-0.020	-0.007	-0.006
HPT2	-0.010	-0.018	0.029	0.025	-0.022	0.014	0.005	0.004
VSAT	0.066	-0.053	0.014	0.273	-0.061	-0.200	0.201	0.163
NS1	-0.107	0.023	0.051	0.044	-0.033	0.012	0.031	0.025
NS2	-0.067	-0.088	0.155	0.142	-0.066	-0.037	0.059	0.048
DR1	-0.027	-0.136	0.182	0.222	-0.009	-0.242	0.055	0.044
DR2	0.058	-0.184	0.177	0.199	-0.007	-0.219	0.101	0.082
LCIP	-0.271	0.089	0.095	0.034	-0.047	0.052	0.072	0.058
LCIN	-0.091	0.101	-0.053	0.127	-0.169	0.184	0.015	0.012
UNIT1	-0.148	0.197	-0.126	-0.023	0.019	-0.010	-0.059	-0.048
UNIT2	-0.037	0.015	0.010	-0.051	-0.003	0.065	0.106	0.086
UNIT3	0.068	0.050	-0.111	-0.122	0.057	0.031	-0.020	-0.016
UNIT4	0.010	-0.018	0.014	-0.101	0.029	0.062	-0.076	-0.062
FINAL	-0.066	0.075	-0.041	0.011	0.037	-0.085	0.004	0.003

FINAL RESIDUAL MATRIX FOR FEMALES

VARIATE	PUMP	PUMN	RQMA	RQPS	AIKP	AIKN	CLMP	CLMN
HSPC	0.002	-0.014	0.082	-0.016	0.013	0.003	0.004	-0.041
HSCA	-0.005	0.038	-0.039	0.008	0.014	0.015	0.019	0.050
HSPS	0.005	-0.035	-0.014	0.003	-0.027	-0.021	-0.026	-0.030
QSAT	-0.014	0.104	-0.099	0.020	0.013	0.071	0.087	0.147
ALG	0.015	-0.117	0.060	-0.012	0.037	-0.026	0.047	0.001
TRIG	-0.014	0.109	-0.002	0.000	-0.089	-0.032	-0.194	-0.174
SMDP	-0.022	0.166	-0.124	0.025	-0.104	-0.126	-0.233	-0.145
SMDN	-0.018	0.134	-0.101	0.020	-0.084	-0.103	-0.189	-0.118
PUMP	0.006	-0.048	0.011	-0.002	0.006	-0.005	0.010	-0.003
PUMN	-0.048	0.364	-0.086	0.017	-0.048	0.038	-0.079	0.020
RQMA	0.011	-0.086	0.675	-0.134	0.043	-0.084	0.023	-0.057
RQPS	-0.002	0.017	-0.134	0.027	-0.009	0.017	-0.005	0.011
AIKP	0.006	-0.048	0.043	-0.009	0.098	0.062	0.172	0.149
AIKN	-0.005	0.038	-0.084	0.017	0.062	0.262	0.187	0.256
CLMP	0.010	-0.079	0.023	-0.005	0.172	0.187	0.519	0.374
CLMN	-0.003	0.020	-0.057	0.011	0.149	0.256	0.374	0.488
EFMP	0.012	-0.090	-0.085	0.017	-0.019	-0.043	0.064	0.024
EFMN	-0.009	0.069	-0.095	0.019	-0.079	-0.020	0.018	0.052
CR1	0.001	-0.009	0.013	-0.003	-0.015	0.006	-0.026	-0.020
CR2	-0.005	0.034	-0.026	0.005	0.022	-0.019	0.041	0.030
PSVR	0.019	-0.146	0.020	-0.004	0.038	0.055	0.057	0.061
GEFT2	0.003	-0.022	0.006	-0.001	-0.004	-0.013	-0.012	-0.020
GEFT3	-0.008	0.061	-0.017	0.003	0.011	0.036	0.032	0.057
HPT1	0.015	-0.117	0.029	-0.006	-0.008	-0.075	-0.052	-0.061
HPT2	-0.011	0.085	-0.021	0.004	0.006	0.054	0.038	0.045
VSAT	-0.009	0.068	-0.113	0.022	-0.082	-0.065	0.005	-0.009
NS1	0.007	-0.057	-0.051	0.010	-0.005	-0.032	-0.011	-0.040
NS2	0.021	-0.157	0.052	-0.010	0.021	-0.007	0.081	0.003
DR1	0.008	-0.061	-0.005	0.001	-0.070	-0.068	-0.092	-0.065
DR2	0.008	-0.059	-0.003	0.001	-0.048	-0.053	-0.040	-0.065
LCIP	-0.001	0.009	-0.250	0.050	-0.004	0.063	0.057	0.130
LCIN	-0.002	0.019	-0.027	0.005	-0.001	0.079	0.014	0.050
UNIT1	-0.004	0.028	0.057	-0.011	0.034	0.078	0.080	0.095
UNIT2	-0.002	0.012	0.025	-0.005	-0.019	0.055	-0.077	0.012
UNIT3	0.017	-0.129	0.003	-0.001	-0.002	-0.008	-0.008	-0.047
UNIT4	0.016	-0.124	-0.070	0.014	0.015	0.007	0.017	0.022
FINAL	0.008	-0.060	-0.014	0.003	-0.001	0.074	0.062	0.096

FINAL RESIDUAL MATRIX FOR FEMALES

VARIATE	EFMP	EFMN	CR1	CR2	PSVR	GEFT2	GEFT3	HPT1
HSPC	-0.091	-0.072	-0.039	0.068	0.030	-0.007	0.019	0.014
HSCA	0.010	0.006	0.031	-0.056	-0.008	-0.010	0.026	0.024
HSPS	0.055	0.046	-0.008	0.017	-0.013	0.016	-0.045	-0.040
QSAT	0.062	0.089	-0.001	0.003	-0.015	0.011	-0.030	-0.034
ALG	0.026	-0.051	-0.007	0.010	0.023	-0.001	0.002	0.030
TRIG	-0.124	-0.003	0.015	-0.025	-0.028	-0.011	0.031	-0.020
SMDP	-0.064	0.102	-0.024	0.042	0.011	-0.012	0.032	-0.007
SMDN	-0.052	0.083	-0.019	0.034	0.009	-0.009	0.026	-0.006
PUMP	0.012	-0.009	0.001	-0.005	0.019	0.003	-0.008	0.015
PUMN	-0.090	0.069	-0.009	0.034	-0.146	-0.022	0.061	-0.117
BQMA	-0.085	-0.095	0.013	-0.026	0.020	0.006	-0.017	0.029
RQPS	0.017	0.019	-0.003	0.005	-0.004	-0.001	0.003	-0.006
AIKP	-0.019	-0.079	-0.015	0.022	0.038	-0.004	0.011	-0.008
AIKN	-0.043	-0.020	0.006	-0.019	0.055	-0.013	0.036	-0.075
CLMP	0.064	0.018	-0.026	0.041	0.057	-0.012	0.032	-0.052
CLMN	0.024	0.052	-0.020	0.030	0.061	-0.020	0.057	-0.061
EFMP	0.352	0.143	0.008	-0.007	-0.053	0.012	-0.033	0.009
EFMN	0.143	0.270	0.003	0.001	-0.055	-0.004	0.012	-0.008
CR1	0.008	0.003	0.055	-0.093	-0.066	0.013	-0.035	-0.019
CR2	-0.007	0.001	-0.093	0.167	0.028	-0.020	0.055	0.030
PSVR	-0.053	-0.055	-0.066	0.028	0.749	-0.028	0.077	0.037
GEFT2	0.012	-0.004	0.013	-0.020	-0.028	0.037	-0.102	-0.005
GEFT3	-0.033	0.012	-0.035	0.055	0.077	-0.102	0.284	0.013
HPT1	0.009	-0.008	-0.019	0.030	0.037	-0.005	0.013	0.162
HPT2	-0.007	0.006	0.014	-0.022	-0.027	0.003	-0.009	-0.118
VSAT	0.168	0.251	-0.053	0.084	0.103	-0.007	0.020	-0.027
NS1	0.194	0.004	-0.013	0.001	0.183	0.010	-0.027	-0.019
NS2	0.010	-0.006	-0.006	0.011	-0.002	-0.002	0.005	0.081
DR1	0.177	0.128	-0.026	0.028	0.157	0.064	-0.178	-0.014
DR2	0.101	0.086	-0.041	0.059	0.130	0.028	-0.077	-0.002
LCIP	0.258	0.117	0.017	-0.005	-0.205	0.023	-0.065	-0.015
LCIN	-0.053	-0.002	0.060	-0.085	-0.198	0.052	-0.145	-0.121
UNIT1	-0.024	-0.018	0.051	-0.102	0.063	0.006	-0.016	-0.075
UNIT2	0.021	-0.015	0.001	0.016	-0.140	-0.005	0.013	-0.005
UNIT3	0.108	-0.028	0.007	-0.009	-0.029	-0.009	0.026	0.026
UNIT4	0.075	-0.012	0.008	-0.002	-0.106	-0.016	0.045	0.013
FINAL	0.098	0.071	0.014	-0.024	-0.020	-0.006	0.016	0.008

FINAL RESIDUAL MATRIX FOR FEMALES

VARIATE	HPT2	VSAT	NS1	NS2	DR1	DR2	LCIP	LCIN
HSPC	-0.010	0.066	-0.107	-0.067	-0.027	0.058	-0.271	-0.091
HSCA	-0.018	-0.053	0.023	-0.088	-0.136	-0.184	0.089	0.101
HSPS	0.029	0.014	0.051	0.155	0.182	0.177	0.095	-0.053
QSAT	0.025	0.273	0.044	0.142	0.222	0.199	0.034	0.127
ALG	-0.022	-0.061	-0.033	-0.066	-0.009	-0.007	-0.047	-0.169
TRIG	0.014	-0.200	0.012	-0.037	-0.242	-0.219	0.052	0.184
SMDP	0.005	0.201	0.031	0.059	0.055	0.101	0.072	0.015
SMDN	0.004	0.163	0.025	0.048	0.044	0.082	0.058	0.012
PUMP	-0.011	-0.009	0.007	0.021	0.008	0.008	-0.001	-0.002
PUMN	0.085	0.068	-0.057	-0.157	-0.061	-0.059	0.009	0.019
RQMA	-0.021	-0.113	-0.051	0.052	-0.005	-0.003	-0.250	-0.027
RQPS	0.004	0.022	0.010	-0.010	0.001	0.001	0.050	0.005
AIKP	0.006	-0.082	-0.005	0.021	-0.070	-0.048	-0.004	-0.001
AIKN	0.054	-0.065	-0.032	-0.007	-0.068	-0.053	0.063	0.079
CLMP	0.038	0.005	-0.011	0.081	-0.092	-0.040	0.057	0.014
CLMN	0.045	-0.009	-0.040	0.003	-0.065	-0.065	0.130	0.050
EFMP	-0.007	0.168	0.194	0.010	0.177	0.101	0.258	-0.053
EFMN	0.006	0.251	0.004	-0.006	0.128	0.086	0.117	-0.002
CR1	0.014	-0.053	-0.013	-0.006	-0.026	-0.041	0.017	0.060
CR2	-0.022	0.084	0.001	0.011	0.028	0.059	-0.005	-0.085
PSVR	-0.027	0.103	0.183	-0.002	0.157	0.130	-0.205	-0.198
GEFT2	0.003	-0.007	0.010	-0.002	0.064	0.028	0.023	0.052
GEFT3	-0.009	0.020	-0.027	0.005	-0.178	-0.077	-0.065	-0.145
HPT1	-0.118	-0.027	-0.019	0.081	-0.014	-0.002	-0.015	-0.121
HPT2	0.086	0.020	0.014	-0.059	0.010	0.001	0.011	0.088
VSAT	0.020	0.899	0.170	0.290	0.346	0.328	0.046	0.131
NS1	0.014	0.170	0.853	0.253	0.102	0.068	0.380	0.089
NS2	-0.059	0.290	0.253	0.810	0.101	0.052	0.244	0.246
DR1	0.010	0.346	0.102	0.101	0.912	0.573	0.124	0.098
DR2	0.001	0.328	0.068	0.052	0.573	0.765	-0.020	-0.106
LCIP	0.011	0.046	0.380	0.244	0.124	-0.020	0.839	0.175
LCIN	0.088	0.131	0.089	0.246	0.098	-0.106	0.175	0.754
UNIT1	0.055	-0.070	0.020	-0.117	-0.144	-0.013	0.049	0.246
UNIT2	0.004	-0.035	0.116	0.071	-0.033	0.067	0.114	0.160
UNIT3	-0.019	-0.067	0.057	-0.027	-0.175	-0.118	0.092	0.125
UNIT4	-0.009	-0.045	0.059	0.072	-0.247	-0.025	0.186	0.080
FINAL	-0.006	0.060	0.091	0.040	-0.082	0.016	0.110	-0.028

FINAL RESIDUAL MATRIX FOR FEMALES

VARIATE	UNIT1	UNIT2	UNIT3	UNIT4	FINAL
HSPC	-0.148	-0.037	0.068	0.010	-0.066
HSCA	0.197	0.015	0.050	-0.018	0.075
HSPS	-0.126	0.010	-0.111	0.014	-0.041
QSAT	-0.023	-0.051	-0.122	-0.101	0.011
ALG	0.019	-0.003	0.057	0.029	0.037
TRIG	-0.010	0.065	0.031	0.062	-0.085
SMDP	-0.059	0.106	-0.020	-0.076	0.004
SMDN	-0.048	0.086	-0.016	-0.062	0.003
PUMP	-0.004	-0.002	0.017	0.016	0.008
PUMN	0.028	0.012	-0.129	-0.124	-0.060
RQMA	0.057	0.025	0.003	-0.070	-0.014
RQPS	-0.011	-0.005	-0.001	0.014	0.003
AIKP	0.034	-0.019	-0.002	0.015	-0.001
AIKN	0.078	0.055	-0.008	0.007	0.074
CLMP	0.080	-0.077	-0.008	0.017	0.062
CLMN	0.095	0.012	-0.047	0.022	0.096
EFMP	-0.024	0.021	0.108	0.075	0.098
EFMN	-0.018	-0.015	-0.028	-0.012	0.071
CR1	0.051	0.001	0.007	0.008	0.014
CR2	-0.102	0.016	-0.009	-0.002	-0.024
PSVR	0.063	-0.140	-0.029	-0.106	-0.020
GEFT2	0.006	-0.005	-0.009	-0.016	-0.006
GEFT3	-0.016	0.013	0.026	0.045	0.016
HPT1	-0.075	-0.005	0.026	0.013	0.008
HPT2	0.055	0.004	-0.019	-0.009	-0.006
VSAT	-0.070	-0.035	-0.067	-0.045	0.060
NS1	0.020	0.116	0.057	0.059	0.091
NS2	-0.117	0.071	-0.027	0.072	0.040
DR1	-0.144	-0.033	-0.175	-0.247	-0.082
DR2	-0.013	0.067	-0.118	-0.025	0.016
LCIP	0.049	0.114	0.092	0.186	0.110
LCIN	0.246	0.160	0.125	0.080	-0.028
UNIT1	0.734	0.285	0.351	0.308	0.290
UNIT2	0.285	0.689	0.438	0.412	0.345
UNIT3	0.351	0.438	0.708	0.532	0.419
UNIT4	0.308	0.412	0.532	0.634	0.377
FINAL	0.290	0.345	0.419	0.377	0.508

FINAL RESIDUAL MATRIX FOR MALES

VARIATE	HSPC	HSCA	HSPS	QSAT	ALG	TRIG	SMDP	SMDN
HSPC	0.868	-0.048	-0.046	0.077	-0.052	-0.011	-0.024	0.051
HSCA	-0.048	0.294	-0.318	-0.025	0.025	-0.008	0.011	-0.025
HSPS	-0.046	-0.318	0.355	0.018	-0.022	0.010	-0.010	0.021
QSAT	0.077	-0.025	0.018	0.375	-0.141	-0.204	0.014	-0.029
ALG	-0.052	0.025	-0.022	-0.141	0.207	-0.133	-0.007	0.016
TRIG	-0.011	-0.008	0.010	-0.204	-0.133	0.399	-0.005	0.010
SMDP	-0.024	0.011	-0.010	0.014	-0.007	-0.005	0.069	-0.148
SMDN	0.051	-0.025	0.021	-0.029	0.016	0.010	-0.148	0.319
PUMP	0.052	-0.037	0.035	-0.017	0.020	-0.010	0.019	-0.041
PUMN	-0.061	0.044	-0.041	0.020	-0.024	0.011	-0.023	0.049
RQMA	0.032	0.017	-0.022	-0.072	-0.009	0.088	-0.010	0.021
RQPS	0.027	0.014	-0.018	-0.060	-0.007	0.073	-0.008	0.018
AIKP	0.079	-0.009	0.001	0.003	-0.007	0.007	0.030	-0.065
AIKN	0.030	-0.006	0.003	-0.034	-0.022	0.065	0.031	-0.066
CLMP	0.152	0.023	-0.043	-0.043	-0.024	0.078	0.017	-0.037
CLMN	0.004	0.075	-0.083	-0.007	-0.017	0.030	0.032	-0.068
EFMP	0.184	-0.043	0.026	-0.042	0.003	0.041	-0.024	0.051
EFMN	0.027	-0.010	0.008	-0.001	0.007	-0.008	-0.033	0.071
CR1	-0.011	0.052	-0.056	0.007	0.055	-0.083	0.001	-0.002
CR2	0.150	0.011	-0.029	-0.019	0.013	0.003	-0.006	0.013
PSVR	-0.013	-0.023	0.027	-0.001	-0.025	0.035	0.000	-0.001
GEFT2	0.052	0.001	-0.007	-0.047	0.000	0.050	-0.002	0.005
GEFT3	-0.035	-0.001	0.005	0.032	0.000	-0.034	0.002	-0.003
HPT1	-0.001	-0.007	0.008	-0.002	0.008	-0.009	0.001	-0.001
HPT2	-0.004	-0.036	0.040	-0.012	0.043	-0.046	0.003	-0.007
VSAT	0.042	-0.179	0.192	0.195	-0.057	-0.128	0.018	-0.039
NS1	0.016	-0.041	0.044	0.120	-0.047	-0.062	-0.041	0.088
NS2	0.072	0.037	-0.049	0.008	-0.037	0.042	-0.023	0.049
DR1	-0.105	-0.128	0.153	0.121	-0.023	-0.096	-0.039	0.083
DR2	-0.091	-0.004	0.014	0.061	-0.042	-0.007	-0.017	0.037
LCIP	0.191	0.046	-0.072	0.025	-0.100	0.110	0.010	-0.021
LCIN	-0.030	0.056	-0.058	0.045	0.074	-0.149	-0.028	0.060
UNIT1	-0.061	-0.095	0.111	-0.023	0.011	0.009	-0.025	0.054
UNIT2	0.012	-0.036	0.038	-0.041	0.035	-0.005	-0.034	0.072
UNIT3	-0.103	-0.015	0.028	-0.068	0.074	-0.030	-0.003	0.006
UNIT4	0.012	-0.002	0.000	0.044	-0.010	-0.033	-0.003	0.007
FINAL	-0.163	0.033	-0.018	-0.007	-0.001	0.009	0.009	-0.020

FINAL RESIDUAL MATRIX FOR MALES

VARIATE	PUMP	PUMN	ROMA	ROPS	AIKP	AIKN	CLMP	CLMN
HSPC	0.052	-0.061	0.032	0.027	0.079	0.030	0.152	0.004
HSCA	-0.037	0.044	0.017	0.014	-0.009	-0.006	0.023	0.075
HSPS	0.035	-0.041	-0.022	-0.018	0.001	0.003	-0.043	-0.083
QSAT	-0.017	0.020	-0.072	-0.060	0.003	-0.034	-0.043	-0.007
ALG	0.020	-0.024	-0.009	-0.007	-0.007	-0.022	-0.024	-0.017
TRIG	-0.010	0.011	0.088	0.073	0.007	0.065	0.078	0.030
SMDP	0.019	-0.023	-0.010	-0.008	0.030	0.031	0.017	0.032
SMDN	-0.041	0.049	0.021	0.018	-0.065	-0.066	-0.037	-0.068
PUMP	0.076	-0.090	-0.003	-0.003	0.057	0.041	0.053	0.039
PUMN	-0.090	0.107	0.004	0.003	-0.067	-0.049	-0.063	-0.046
ROMA	-0.003	0.004	0.451	0.377	0.019	0.000	0.026	0.034
ROPS	-0.003	0.003	0.377	0.316	0.016	0.000	0.022	0.028
AIKP	0.057	-0.067	0.019	0.016	0.225	0.081	0.190	0.052
AIKN	0.041	-0.049	0.000	0.000	0.081	0.184	0.159	0.109
CLMP	0.053	-0.063	0.026	0.022	0.190	0.159	0.423	0.193
CLMN	0.039	-0.046	0.034	0.028	0.052	0.109	0.193	0.231
EFMP	0.018	-0.021	-0.062	-0.052	0.041	-0.040	0.103	-0.071
EFMN	-0.036	0.043	0.008	0.006	-0.034	-0.078	0.024	-0.059
CR1	-0.022	0.026	-0.042	-0.035	-0.036	-0.053	-0.021	-0.013
CR2	0.006	-0.008	-0.040	-0.034	0.037	-0.011	0.009	0.007
PSVR	0.008	-0.010	0.023	0.019	0.011	0.024	0.008	0.004
GEFT2	0.007	-0.009	-0.044	-0.037	-0.066	-0.021	-0.006	-0.027
GEFT3	-0.005	0.006	0.030	0.025	0.044	0.014	0.004	0.018
HPT1	0.005	-0.005	-0.011	-0.009	-0.001	0.004	-0.001	-0.001
HPT2	0.024	-0.028	-0.055	-0.046	-0.006	0.021	-0.003	-0.003
VSAT	0.013	-0.015	-0.087	-0.073	0.039	0.045	-0.077	-0.124
NS1	-0.073	0.087	-0.136	-0.114	-0.094	-0.068	-0.101	-0.099
NS2	-0.060	0.071	-0.143	-0.119	0.007	-0.048	0.057	-0.035
DR1	-0.017	0.021	-0.125	-0.105	-0.001	-0.008	-0.098	-0.127
DR2	-0.025	0.030	-0.042	-0.035	0.004	-0.019	-0.014	-0.071
LCIP	-0.008	0.009	-0.027	-0.023	0.076	0.040	0.152	0.017
LCIN	-0.062	0.073	0.069	0.057	-0.072	-0.096	0.023	0.074
UNIT1	0.012	-0.014	0.100	0.084	-0.085	-0.037	0.022	0.013
UNIT2	0.017	-0.020	0.119	0.100	-0.038	-0.048	-0.060	-0.015
UNIT3	0.043	-0.050	0.063	0.052	0.006	0.057	0.040	0.051
UNIT4	0.029	-0.035	0.026	0.022	-0.048	0.020	-0.019	0.047
FINAL	0.005	-0.005	0.000	0.000	-0.046	-0.033	-0.099	-0.020

FINAL RESIDUAL MATRIX FOR MALES

VARIATE	EFMP	EFMN	CR1	CR2	PSVR	GEFT2	GEFT3	HPT1
HSPC	0.184	0.027	-0.011	0.150	-0.013	0.052	-0.035	-0.001
HSCA	-0.043	-0.010	0.052	0.011	-0.023	0.001	-0.001	-0.007
HSPS	0.026	0.008	-0.056	-0.029	0.027	-0.007	0.005	0.008
QSAT	-0.042	-0.001	0.007	-0.019	-0.001	-0.047	0.032	-0.002
ALG	0.003	0.007	0.055	0.013	-0.025	0.000	0.000	0.008
TRIG	0.041	-0.008	-0.083	0.003	0.035	0.050	-0.034	-0.009
SMDP	-0.024	-0.033	0.001	-0.006	0.000	-0.002	0.002	0.001
SMDN	0.051	0.071	-0.002	0.013	-0.001	0.005	-0.003	-0.001
PUMP	0.018	-0.036	-0.022	0.006	0.008	0.007	-0.005	0.005
PUMN	-0.021	0.043	0.026	-0.008	-0.010	-0.009	0.006	-0.005
RQMA	-0.062	0.008	-0.042	-0.040	0.023	-0.044	0.030	-0.011
RQPS	-0.052	0.006	-0.035	-0.034	0.019	-0.037	0.025	-0.009
AIKP	0.041	-0.034	-0.036	0.037	0.011	-0.066	0.044	-0.001
AIKN	-0.040	-0.078	-0.053	-0.011	0.024	-0.021	0.014	0.004
CLMP	0.103	0.024	-0.021	0.009	0.008	-0.006	0.004	-0.001
CLMN	-0.071	-0.059	-0.013	0.007	0.004	-0.027	0.018	-0.001
EFMP	0.296	0.068	0.009	0.083	-0.014	0.069	-0.046	0.004
EFMN	0.068	0.107	0.038	-0.027	-0.013	0.038	-0.025	-0.003
CR1	0.009	0.038	0.580	0.373	-0.289	0.056	-0.037	0.003
CR2	0.083	-0.027	0.373	0.583	-0.227	0.049	-0.033	0.007
PSVR	-0.014	-0.013	-0.289	-0.227	0.149	-0.029	0.020	-0.002
GEFT2	0.069	0.038	0.056	0.049	-0.029	0.251	-0.168	0.006
GEFT3	-0.046	-0.025	-0.037	-0.033	0.020	-0.168	0.113	-0.004
HPT1	0.004	-0.003	0.003	0.007	-0.002	0.006	-0.004	0.022
HPT2	0.020	-0.017	0.015	0.035	-0.011	0.033	-0.022	0.112
VSAT	0.025	-0.038	-0.024	0.012	0.009	-0.027	0.018	0.024
NS1	-0.035	0.072	-0.017	-0.073	0.016	-0.112	0.075	-0.022
NS2	0.108	0.072	0.165	0.087	-0.080	-0.028	0.018	0.014
DR1	0.038	-0.006	0.074	-0.028	-0.028	-0.019	0.013	-0.011
DR2	0.015	0.039	0.067	-0.073	-0.019	0.019	-0.013	-0.009
LCIP	0.151	0.022	0.133	0.242	-0.085	0.111	-0.075	0.011
LCIN	-0.063	0.081	0.150	0.031	-0.067	0.044	-0.029	-0.007
UNIT1	0.006	0.070	0.095	-0.003	-0.040	-0.013	0.008	0.015
UNIT2	-0.066	0.022	0.035	0.035	-0.019	0.022	-0.015	0.005
UNIT3	-0.076	-0.019	0.040	0.027	-0.020	-0.006	0.004	0.000
UNIT4	-0.070	-0.021	-0.023	-0.020	0.012	-0.022	0.014	-0.001
FINAL	-0.053	-0.018	0.030	0.056	-0.020	0.003	-0.002	0.013

FINAL RESIDUAL MATRIX FOR MALES

VARIATE	HPT2	VSAT	NS1	NS2	DR1	DR2	LCIP	LCIN
HSPC	-0.004	0.042	0.016	0.072	-0.105	-0.091	0.191	-0.030
HSCA	-0.036	-0.179	-0.041	0.037	-0.128	-0.004	0.046	0.056
HSPS	0.040	0.192	0.044	-0.049	0.153	0.014	-0.072	-0.058
OSAT	-0.012	0.195	0.120	0.008	0.121	0.061	0.025	0.045
ALG	0.043	-0.057	-0.047	-0.037	-0.023	-0.042	-0.100	0.074
TRIG	-0.046	-0.128	-0.062	0.042	-0.096	-0.007	0.110	-0.149
SMDP	0.003	0.018	-0.041	-0.023	-0.039	-0.017	0.010	-0.028
SMDN	-0.007	-0.039	0.088	0.049	0.083	0.037	-0.021	0.060
PUMP	0.024	0.013	-0.073	-0.060	-0.017	-0.025	-0.008	-0.062
PUMN	-0.028	-0.015	0.087	0.071	0.021	0.030	0.009	0.073
RQMA	-0.055	-0.087	-0.136	-0.143	-0.125	-0.042	-0.027	0.069
RQPS	-0.046	-0.073	-0.114	-0.119	-0.105	-0.035	-0.023	0.057
AIKP	-0.006	0.039	-0.094	0.007	-0.001	0.004	0.076	-0.072
AIKN	0.021	0.045	-0.068	-0.048	-0.008	-0.019	0.040	-0.096
CLMP	-0.003	-0.077	-0.101	0.057	-0.098	-0.014	0.152	0.023
CLMN	-0.003	-0.124	-0.099	-0.035	-0.127	-0.071	0.017	0.074
EFMP	0.020	0.025	-0.035	0.108	0.038	0.015	0.151	-0.063
EFMN	-0.017	-0.038	0.072	0.072	-0.006	0.039	0.022	0.081
CR1	0.015	-0.024	-0.017	0.165	0.074	0.067	0.133	0.150
CR2	0.035	0.012	-0.073	0.087	-0.028	-0.073	0.242	0.031
PSVR	-0.011	0.009	0.016	-0.080	-0.028	-0.019	-0.085	-0.067
GEFT2	0.033	-0.027	-0.112	-0.028	-0.019	0.019	0.111	0.044
GEFT3	-0.022	0.018	0.075	0.018	0.013	-0.013	-0.075	-0.029
HPT1	0.112	0.024	-0.022	0.014	-0.011	-0.009	0.011	-0.007
HPT2	0.577	0.123	-0.115	0.072	-0.055	-0.049	0.056	-0.037
VSAT	0.123	0.890	0.192	-0.012	0.274	0.220	-0.135	-0.233
NS1	-0.115	0.192	0.872	0.348	0.130	0.272	0.041	-0.116
NS2	0.072	-0.012	0.348	0.862	0.173	0.245	0.257	-0.172
DR1	-0.055	0.274	0.130	0.173	0.708	0.403	-0.041	-0.286
DR2	-0.049	0.220	0.272	0.245	0.403	0.775	0.034	-0.155
LCIP	0.056	-0.135	0.041	0.257	-0.041	0.034	0.653	-0.052
LCIN	-0.037	-0.233	-0.116	-0.172	-0.286	-0.155	-0.052	0.853
UNIT1	0.079	0.085	0.113	0.194	-0.031	0.120	0.039	0.093
UNIT2	0.027	0.024	-0.059	-0.072	-0.027	0.199	-0.088	-0.021
UNIT3	0.000	0.100	-0.010	0.054	-0.026	0.193	0.015	-0.030
UNIT4	-0.006	0.087	0.074	-0.073	-0.046	0.113	-0.006	-0.068
FINAL	0.065	0.037	-0.049	-0.023	-0.022	0.129	-0.008	0.004

FINAL RESIDUAL MATRIX FOR MALES

VARIATE	UNIT1	UNIT2	UNIT3	UNIT4	FINAL
HSPC	-0.061	0.012	-0.103	0.012	-0.163
HSCA	-0.095	-0.036	-0.015	-0.002	0.033
HSPS	0.111	0.038	0.028	0.000	-0.018
QSAT	-0.023	-0.041	-0.068	0.044	-0.007
ALG	0.011	0.035	0.074	-0.010	-0.001
TRIG	0.009	-0.005	-0.030	-0.033	0.009
SMDP	-0.025	-0.034	-0.003	-0.003	0.009
SMDN	0.054	0.072	0.006	0.007	-0.020
PUMP	0.012	0.017	0.043	0.029	0.005
PUMN	-0.014	-0.020	-0.050	-0.035	-0.005
RQMA	0.100	0.119	0.063	0.026	0.000
RQPS	0.084	0.100	0.052	0.022	0.000
AIKP	-0.085	-0.038	0.006	-0.048	-0.046
AIKN	-0.037	-0.048	0.057	0.020	-0.033
CLMP	0.022	-0.060	0.040	-0.019	-0.099
CLMN	0.013	-0.015	0.051	0.047	-0.020
EFMP	0.006	-0.066	-0.076	-0.070	-0.053
EFMN	0.070	0.022	-0.019	-0.021	-0.018
CR1	0.095	0.035	0.040	-0.023	0.030
CR2	-0.003	0.035	0.027	-0.020	0.056
PSVR	-0.040	-0.019	-0.020	0.012	-0.020
GEFT2	-0.013	0.022	-0.006	-0.022	0.003
GEFT3	0.008	-0.015	0.004	0.014	-0.002
HPT1	0.015	0.005	0.000	-0.001	0.013
HPT2	0.079	0.027	0.000	-0.006	0.065
VSAT	0.085	0.024	0.100	0.087	0.037
NS1	0.113	-0.059	-0.010	0.074	-0.049
NS2	0.194	-0.072	0.054	-0.073	-0.023
DR1	-0.031	-0.027	-0.026	-0.046	-0.022
DR2	0.120	0.199	0.193	0.113	0.129
LCIP	0.039	-0.088	0.015	-0.006	-0.008
LCIN	0.093	-0.021	-0.030	-0.068	0.004
UNIT1	0.780	0.341	0.502	0.303	0.281
UNIT2	0.341	0.708	0.465	0.352	0.327
UNIT3	0.502	0.465	0.767	0.422	0.397
UNIT4	0.303	0.352	0.422	0.607	0.294
FINAL	0.281	0.327	0.397	0.294	0.480

Table 21. Factor theory correlation matrices

FACTOR THEORY CORRELATION MATRIX FOR FEMALES

VARIATE	HSPC	HSCA	HSPS	QSAT	ALG	TRIG	SMDP	SMDN
HSPC	0.520	0.428	0.401	0.097	0.010	0.096	0.095	0.060
HSCA	0.428	0.617	0.544	0.237	0.149	0.151	0.099	0.022
HSPS	0.401	0.544	0.612	0.223	0.179	0.161	0.110	0.089
QSAT	0.097	0.237	0.223	0.541	0.630	0.419	0.033	-0.026
ALG	0.010	0.149	0.179	0.630	0.820	0.545	0.013	0.010
TRIG	0.096	0.151	0.161	0.419	0.545	0.419	-0.024	0.044
SMDP	0.095	0.099	0.110	0.033	0.013	-0.024	0.156	-0.117
SMDN	0.060	0.022	0.089	-0.026	0.010	0.044	-0.117	0.445
PUMP	0.503	0.183	0.292	0.189	0.254	0.283	0.121	0.143
PUMN	0.322	0.120	0.242	0.224	0.298	0.246	0.118	0.174
RQMA	0.111	0.197	0.294	0.221	0.306	0.238	0.066	0.075
RQPS	0.005	0.113	0.299	0.202	0.341	0.278	0.110	0.017
AIKP	0.216	0.278	0.298	0.317	0.305	0.219	0.124	0.241
AIKN	0.040	0.213	0.264	0.343	0.367	0.230	0.091	0.159
CLMP	0.255	0.266	0.330	0.313	0.385	0.301	0.112	0.134
CLMN	0.095	0.240	0.283	0.313	0.375	0.275	0.072	0.140
EFMP	0.246	0.156	0.187	0.205	0.230	0.197	0.125	0.209
EFMN	0.213	0.096	0.157	0.146	0.163	0.129	0.091	0.334
CR1	-0.161	-0.232	-0.080	0.054	0.121	0.080	-0.064	-0.083
CR2	-0.080	-0.142	-0.055	0.165	0.235	0.173	-0.045	-0.117
PSVR	-0.013	0.025	0.084	0.175	0.216	0.151	-0.017	0.093
GEFT2	-0.064	0.004	0.138	0.247	0.189	-0.004	0.022	-0.023
GEFT3	-0.150	0.002	0.114	0.256	0.234	0.045	-0.007	-0.036
HPT1	-0.155	-0.014	0.148	0.141	0.259	0.035	0.104	0.018
HPT2	-0.081	-0.090	0.097	0.054	0.185	0.009	0.141	0.087
VSAT	0.011	0.036	0.035	0.114	0.154	0.088	-0.015	0.004
NS1	0.076	0.118	0.067	0.177	0.169	0.115	0.010	-0.134
NS2	0.094	0.073	0.165	0.062	0.088	0.097	-0.040	0.019
DR1	-0.012	0.034	0.045	0.073	0.055	0.044	-0.035	0.017
DR2	0.119	0.114	0.150	0.050	-0.006	-0.031	0.103	-0.063
LCIP	0.005	-0.069	-0.026	-0.005	0.060	0.061	0.010	0.115
LCIN	-0.077	-0.167	-0.109	-0.195	-0.120	-0.051	-0.056	0.090
UNIT1	0.101	0.008	0.080	0.112	0.223	0.212	-0.063	0.200
UNIT2	0.218	0.215	0.285	0.270	0.350	0.302	0.028	0.090
UNIT3	0.155	0.122	0.166	0.217	0.298	0.289	-0.053	0.049
UNIT4	0.234	0.271	0.333	0.327	0.375	0.319	0.015	0.027
FINAL	0.335	0.359	0.404	0.339	0.404	0.365	0.027	0.072

FACTOR THEORY CORRELATION MATRIX FOR FEMALES

VARIATE	PUMP	PUMN	RQMA	RQPS	AIKP	AIKN	CLMP	CLMN
HSPC	0.503	0.322	0.111	0.005	0.216	0.040	0.255	0.095
HSCA	0.183	0.120	0.197	0.113	0.278	0.213	0.266	0.240
HSPS	0.292	0.242	0.294	0.299	0.298	0.264	0.330	0.283
QSAT	0.189	0.224	0.221	0.202	0.317	0.343	0.313	0.313
ALG	0.254	0.298	0.306	0.341	0.305	0.367	0.385	0.375
TRIG	0.283	0.246	0.238	0.278	0.219	0.230	0.301	0.275
SMDP	0.121	0.118	0.066	0.110	0.124	0.091	0.112	0.072
SMDN	0.143	0.174	0.075	0.017	0.241	0.159	0.134	0.140
PUMP	0.994	0.743	0.269	0.327	0.306	0.075	0.438	0.161
PUMN	0.743	0.636	0.262	0.335	0.409	0.241	0.413	0.240
RQMA	0.269	0.262	0.325	0.505	0.265	0.283	0.304	0.307
RQPS	0.327	0.335	0.505	0.973	0.335	0.415	0.366	0.434
AIKP	0.306	0.409	0.265	0.335	0.902	0.758	0.516	0.588
AIKN	0.075	0.241	0.283	0.415	0.758	0.738	0.430	0.572
CLMP	0.438	0.413	0.304	0.366	0.516	0.430	0.481	0.429
CLMN	0.161	0.240	0.307	0.434	0.588	0.572	0.429	0.512
EFMP	0.515	0.506	0.239	0.340	0.684	0.500	0.451	0.417
EFMN	0.483	0.516	0.191	0.235	0.705	0.502	0.414	0.382
CR1	-0.144	-0.114	-0.044	-0.065	-0.063	0.063	0.063	0.070
CR2	-0.054	-0.056	-0.026	-0.084	0.004	0.092	0.131	0.114
PSVR	0.004	0.068	0.089	0.085	0.281	0.300	0.208	0.253
GEFT2	-0.135	0.040	-0.042	-0.158	0.125	0.207	-0.033	-0.003
GEFT3	-0.227	-0.037	0.026	0.011	0.105	0.238	-0.041	0.056
HPT1	-0.152	0.005	0.106	0.038	0.000	0.129	0.147	0.125
HPT2	0.066	0.168	0.100	0.038	0.093	0.130	0.236	0.143
VSAT	0.058	0.048	0.028	-0.017	-0.094	-0.076	-0.008	-0.049
NS1	0.042	0.004	0.005	-0.049	-0.074	-0.054	-0.007	-0.040
NS2	0.157	0.086	0.101	0.134	-0.127	-0.087	0.025	-0.030
DR1	-0.089	-0.050	0.006	-0.006	0.106	0.134	0.038	0.092
DR2	0.031	0.051	-0.001	-0.064	0.182	0.157	0.130	0.105
LCIP	0.143	0.133	0.061	0.083	0.152	0.108	0.161	0.133
LCIN	0.034	-0.023	-0.004	0.032	-0.221	-0.208	-0.049	-0.096
UNIT1	0.336	0.253	0.143	0.147	0.049	0.007	0.184	0.094
UNIT2	0.398	0.319	0.267	0.336	0.233	0.201	0.326	0.258
UNIT3	0.318	0.204	0.185	0.237	0.034	0.032	0.188	0.123
UNIT4	0.326	0.254	0.249	0.294	0.224	0.222	0.303	0.257
FINAL	0.470	0.342	0.302	0.337	0.213	0.172	0.356	0.260

FACTOR THEORY CORRELATION MATRIX FOR FEMALES

VARIATE	EFMP	EFMN	CR1	CR2	PSVR	GEFT2	GEFT3	HPT1
HSPC	0.246	0.213	-0.161	-0.080	-0.013	-0.064	-0.150	-0.155
HSCA	0.156	0.096	-0.232	-0.142	0.025	0.004	0.002	-0.014
HSPS	0.187	0.157	-0.080	-0.055	0.084	0.138	0.114	0.148
QSAT	0.205	0.146	0.054	0.165	0.175	0.247	0.256	0.141
ALG	0.230	0.163	0.121	0.235	0.216	0.189	0.234	0.259
TRIG	0.197	0.129	0.080	0.173	0.151	-0.004	0.045	0.035
SMDP	0.125	0.091	-0.064	-0.045	-0.017	0.022	-0.007	0.104
SMDN	0.209	0.334	-0.083	-0.117	0.093	-0.023	-0.036	0.018
PUMP	0.515	0.483	-0.144	-0.054	0.004	-0.135	-0.227	-0.152
PUMN	0.506	0.516	-0.114	-0.056	0.068	0.040	-0.037	0.005
RQMA	0.239	0.191	-0.044	-0.026	0.089	-0.042	0.026	0.106
RQPS	0.340	0.235	-0.065	-0.084	0.085	-0.158	0.011	0.038
AIKP	0.684	0.705	-0.063	0.004	0.281	0.125	0.105	0.000
AIKN	0.500	0.502	0.063	0.092	0.300	0.207	0.238	0.129
CLMP	0.451	0.414	0.063	0.131	0.208	-0.033	-0.041	0.147
CLMN	0.417	0.382	0.070	0.114	0.253	-0.003	0.056	0.125
EFMP	0.648	0.654	-0.169	-0.095	0.144	-0.075	-0.095	-0.106
EFMN	0.654	0.730	-0.183	-0.142	0.153	0.034	-0.026	-0.050
CR1	-0.169	-0.183	0.945	0.858	0.347	0.251	0.181	0.382
CR2	-0.095	-0.142	0.858	0.833	0.340	0.184	0.119	0.309
PSVR	0.144	0.153	0.347	0.340	0.251	0.141	0.124	0.181
GEFT2	-0.075	0.034	0.251	0.184	0.141	0.963	0.792	0.339
GEFT3	-0.095	-0.026	0.181	0.119	0.124	0.792	0.716	0.270
HPT1	-0.106	-0.050	0.382	0.309	0.181	0.339	0.270	0.838
HPT2	0.059	0.130	0.408	0.338	0.196	0.193	0.087	0.810
VSAT	-0.058	-0.053	-0.099	-0.075	-0.049	0.083	0.077	0.065
NS1	-0.072	-0.120	-0.043	0.014	-0.034	0.119	0.109	-0.042
NS2	-0.087	-0.099	0.094	0.069	0.003	0.106	0.098	0.031
DR1	0.006	0.007	0.183	0.173	0.118	0.132	0.125	0.017
DR2	0.080	0.079	0.252	0.243	0.134	0.206	0.114	0.197
LCIP	0.169	0.179	0.144	0.143	0.109	-0.162	-0.163	0.102
LCIN	-0.099	-0.086	0.093	0.044	-0.033	-0.292	-0.258	0.079
UNIT1	0.133	0.145	0.052	0.071	0.066	-0.128	-0.123	0.043
UNIT2	0.239	0.189	0.053	0.104	0.118	-0.038	-0.021	0.048
UNIT3	0.083	0.023	0.092	0.139	0.072	-0.082	-0.048	-0.073
UNIT4	0.173	0.108	0.147	0.199	0.153	0.097	0.101	0.034
FINAL	0.221	0.145	-0.005	0.077	0.097	-0.045	-0.028	-0.003

FACTOR THEORY CORRELATION MATRIX FOR FEMALES

VARIATE	HPT2	VSAT	NS1	NS2	DR1	DR2	LCIP	LCIN
HSPC	-0.081	0.011	0.076	0.094	-0.012	0.119	0.005	-0.077
HSCA	-0.090	0.036	0.118	0.073	0.034	0.114	-0.069	-0.167
HSPS	0.097	0.035	0.067	0.165	0.045	0.150	-0.026	-0.109
QSAT	0.054	0.114	0.177	0.062	0.073	0.050	-0.005	-0.195
ALG	0.185	0.154	0.169	0.088	0.055	-0.006	0.060	-0.120
TRIG	0.009	0.088	0.115	0.097	0.044	-0.031	0.061	-0.051
SMDP	0.141	-0.015	0.010	-0.040	-0.035	0.103	0.010	-0.056
SMDN	0.087	0.004	-0.134	0.019	0.017	-0.063	0.115	0.090
PUMP	0.066	0.058	0.042	0.157	-0.089	0.031	0.143	0.034
PUMN	0.168	0.048	0.004	0.086	-0.050	0.051	0.133	-0.023
ROMA	0.100	0.028	0.005	0.101	0.006	-0.001	0.061	-0.004
ROPS	0.038	-0.017	-0.049	0.134	-0.006	-0.064	0.083	0.032
AIKP	0.093	-0.094	-0.074	-0.127	0.106	0.182	0.152	-0.221
AIKN	0.130	-0.076	-0.054	-0.087	0.134	0.157	0.108	-0.208
CLMP	0.236	-0.008	-0.007	0.025	0.038	0.130	0.161	-0.049
CLMN	0.143	-0.049	-0.040	-0.030	0.092	0.105	0.133	-0.096
EFMP	0.059	-0.058	-0.072	-0.087	0.006	0.080	0.169	-0.099
EFMN	0.130	-0.053	-0.120	-0.099	0.007	0.079	0.179	-0.086
CR1	0.408	-0.099	-0.043	0.094	0.183	0.252	0.144	0.093
CR2	0.338	-0.075	0.014	0.069	0.173	0.243	0.143	0.044
PSVR	0.196	-0.049	-0.034	0.003	0.118	0.134	0.109	-0.033
GEFT2	0.193	0.083	0.119	0.106	0.132	0.206	-0.162	-0.292
GEFT3	0.087	0.077	0.109	0.098	0.125	0.114	-0.163	-0.258
HPT1	0.810	0.065	-0.042	0.031	0.017	0.197	0.102	0.079
HPT2	0.914	0.018	-0.119	-0.011	-0.017	0.228	0.213	0.157
VSAT	0.018	0.101	0.077	0.059	-0.034	-0.061	-0.047	-0.012
NS1	-0.119	0.077	0.147	0.059	0.006	-0.004	-0.096	-0.106
NS2	-0.011	0.059	0.059	0.190	0.014	-0.016	-0.040	0.032
DR1	-0.017	-0.034	0.006	0.014	0.088	0.069	0.001	-0.061
DR2	0.228	-0.061	-0.004	-0.016	0.069	0.235	0.037	-0.083
LCIP	0.213	-0.047	-0.096	-0.040	0.001	0.037	0.161	0.107
LCIN	0.157	-0.012	-0.106	0.032	-0.061	-0.083	0.107	0.246
UNIT1	0.113	0.059	-0.014	0.108	-0.020	-0.068	0.116	0.127
UNIT2	0.074	0.046	0.051	0.132	0.022	0.025	0.079	-0.003
UNIT3	-0.076	0.059	0.081	0.165	0.024	-0.049	0.037	0.033
UNIT4	0.007	0.044	0.103	0.166	0.074	0.073	0.025	-0.075
FINAL	-0.008	0.079	0.115	0.187	0.024	0.022	0.038	-0.035

FACTOR THEORY CORRELATION MATRIX FOR FEMALES

VARIATE	UNIT1	UNIT2	UNIT3	UNIT4	FINAL
HSPC	0.101	0.218	0.155	0.234	0.335
HSCA	0.008	0.215	0.122	0.271	0.359
HSPS	0.080	0.285	0.166	0.333	0.404
QSAT	0.112	0.270	0.217	0.327	0.339
ALG	0.223	0.350	0.298	0.375	0.404
TRIG	0.212	0.302	0.289	0.319	0.365
SMDP	-0.063	0.028	-0.053	0.015	0.027
SMDN	0.200	0.090	0.049	0.027	0.072
PUMP	0.336	0.398	0.318	0.326	0.470
PUMN	0.253	0.319	0.204	0.254	0.342
RQMA	0.143	0.267	0.185	0.249	0.302
RQPS	0.147	0.336	0.237	0.294	0.337
AIKP	0.049	0.233	0.034	0.224	0.213
AIKN	0.007	0.201	0.032	0.222	0.172
CLMP	0.184	0.326	0.188	0.303	0.356
CLMN	0.094	0.258	0.123	0.257	0.260
EFMP	0.133	0.239	0.083	0.173	0.221
EFMN	0.145	0.189	0.023	0.108	0.145
CR1	0.052	0.053	0.092	0.147	-0.005
CR2	0.071	0.104	0.139	0.199	0.077
PSVR	0.066	0.118	0.072	0.153	0.097
GEFT2	-0.128	-0.038	-0.082	0.097	-0.045
GEFT3	-0.123	-0.021	-0.048	0.101	-0.028
HPT1	0.043	0.048	-0.073	0.034	-0.003
HPT2	0.113	0.074	-0.076	0.007	-0.008
VSAT	0.059	0.046	0.059	0.044	0.079
NS1	-0.014	0.051	0.081	0.103	0.115
NS2	0.108	0.132	0.165	0.166	0.187
DR1	-0.020	0.022	0.024	0.074	0.024
DR2	-0.068	0.025	-0.049	0.073	0.022
LCIP	0.116	0.079	0.037	0.025	0.038
LCIN	0.127	-0.003	0.033	-0.075	-0.035
UNIT1	0.266	0.211	0.213	0.163	0.235
UNIT2	0.211	0.311	0.261	0.310	0.374
UNIT3	0.213	0.261	0.292	0.279	0.334
UNIT4	0.163	0.310	0.279	0.366	0.397
FINAL	0.235	0.374	0.334	0.397	0.492

FACTOR THEORY CORRELATION MATRIX FOR MALES

VARIATE	HSPC	HSCA	HSPS	QSAT	ALG	TRIG	SMDP	SMDN
HSPC	0.132	0.228	0.159	0.180	0.204	0.182	0.040	0.101
HSCA	0.228	0.706	0.567	0.322	0.268	0.235	0.031	0.044
HSPS	0.159	0.567	0.645	0.321	0.262	0.234	-0.187	-0.183
QSAT	0.180	0.322	0.321	0.625	0.635	0.441	-0.131	-0.040
ALG	0.204	0.268	0.262	0.635	0.793	0.607	-0.019	0.027
TRIG	0.182	0.235	0.234	0.441	0.607	0.601	0.071	0.169
SMDP	0.040	0.031	-0.187	-0.131	-0.019	0.071	0.931	0.671
SMDN	0.101	0.044	-0.183	-0.040	0.027	0.169	0.671	0.681
PUMP	0.242	0.319	0.176	0.389	0.343	0.254	0.017	0.265
PUMN	0.228	0.297	0.179	0.385	0.310	0.249	-0.037	0.257
ROMA	0.217	0.279	0.083	0.294	0.330	0.284	-0.065	0.166
RQPS	0.105	0.259	0.302	0.454	0.367	0.162	0.012	-0.030
AIKP	0.228	0.217	0.279	0.306	0.365	0.422	-0.162	0.131
AIKN	0.228	0.190	0.257	0.350	0.374	0.398	-0.180	0.129
CLMP	0.202	0.201	0.161	0.306	0.304	0.322	-0.184	0.142
CLMN	0.230	0.189	0.231	0.393	0.418	0.421	-0.137	0.162
EFMP	0.221	0.228	0.205	0.213	0.250	0.341	0.097	0.323
EFMN	0.165	0.095	0.161	0.048	0.052	0.218	0.067	0.306
CR1	0.006	0.150	0.196	0.182	0.036	0.097	-0.051	0.056
CR2	0.045	0.201	0.213	0.252	0.122	0.159	-0.052	0.072
PSVR	-0.029	-0.001	0.068	0.258	0.091	0.107	-0.254	-0.032
GEFT2	0.019	0.109	0.030	0.276	0.105	0.073	-0.180	-0.006
GEFT3	0.042	0.109	0.083	0.310	0.153	0.127	-0.126	0.011
HPT1	-0.015	0.174	0.152	-0.033	-0.082	0.137	-0.064	0.087
HPT2	-0.021	0.086	0.096	0.002	-0.027	0.090	-0.101	-0.024
VSAT	0.005	0.032	0.002	0.142	0.169	0.073	0.039	-0.037
NS1	0.057	0.006	0.010	0.183	0.222	0.148	-0.148	-0.045
NS2	0.001	-0.027	-0.080	0.115	0.142	0.110	-0.010	0.018
DR1	0.091	0.130	0.039	0.339	0.347	0.250	-0.054	0.060
DR2	0.087	0.139	0.101	0.297	0.287	0.235	-0.106	0.038
LCIP	0.032	-0.106	-0.068	0.132	0.173	0.217	0.006	0.171
LCIN	-0.010	0.067	0.088	0.078	0.025	0.063	-0.161	-0.072
UNIT1	0.139	0.308	0.273	0.240	0.238	0.165	0.001	0.005
UNIT2	0.133	0.262	0.259	0.337	0.322	0.198	-0.036	-0.017
UNIT3	0.085	0.187	0.265	0.175	0.139	0.138	-0.002	0.017
UNIT4	0.130	0.301	0.342	0.285	0.271	0.208	0.081	0.045
FINAL	0.200	0.320	0.339	0.462	0.508	0.384	0.053	0.081

FACTOR THEORY CORRELATION MATRIX FOR MAIFS

VARIATE	PUMP	PUMN	RQMA	RQPS	AIKP	AIKN	CLMP	CLMN
HSPC	0.242	0.228	0.217	0.105	0.228	0.228	0.202	0.230
HSCA	0.319	0.297	0.279	0.259	0.217	0.190	0.201	0.189
HSPS	0.176	0.179	0.083	0.302	0.279	0.257	0.161	0.231
QSAT	0.389	0.385	0.294	0.454	0.306	0.350	0.306	0.393
AIG	0.343	0.310	0.330	0.367	0.365	0.374	0.304	0.418
TRIG	0.254	0.249	0.284	0.162	0.422	0.398	0.322	0.421
SMDP	0.017	-0.037	-0.065	0.012	-0.162	-0.180	-0.184	-0.137
SMDN	0.265	0.257	0.166	-0.030	0.131	0.129	0.142	0.162
PUMP	0.924	0.894	0.393	0.484	0.546	0.603	0.588	0.580
PUMN	0.894	0.893	0.391	0.447	0.570	0.630	0.607	0.612
RQMA	0.393	0.391	0.549	-0.006	0.367	0.377	0.414	0.407
RQPS	0.484	0.447	-0.006	0.684	0.152	0.227	0.165	0.228
AIKP	0.546	0.570	0.367	0.152	0.775	0.782	0.604	0.743
AIKN	0.603	0.630	0.377	0.227	0.782	0.816	0.632	0.783
CLMP	0.588	0.607	0.414	0.165	0.604	0.632	0.577	0.612
CLMN	0.580	0.612	0.407	0.228	0.743	0.783	0.612	0.769
EFMP	0.620	0.616	0.303	0.216	0.668	0.684	0.548	0.641
EFMN	0.554	0.572	0.170	0.147	0.703	0.722	0.527	0.652
CR1	0.102	0.174	-0.032	0.193	0.066	0.093	0.104	0.111
CR2	0.206	0.253	0.041	0.263	0.111	0.146	0.175	0.160
PSVR	0.014	0.152	0.074	0.057	0.071	0.115	0.139	0.176
GEFT2	0.087	0.131	0.185	0.156	-0.074	-0.004	0.139	0.048
GEFT3	0.062	0.094	0.167	0.215	0.004	0.088	0.157	0.135
HPT1	0.126	0.141	-0.082	0.030	0.024	-0.024	0.126	-0.071
HPT2	-0.016	-0.014	-0.056	0.011	-0.031	-0.053	0.043	-0.079
VSAT	-0.049	-0.072	0.018	0.096	-0.125	-0.116	-0.080	-0.085
NS1	0.192	0.193	0.156	0.080	0.179	0.191	0.178	0.196
NS2	-0.049	-0.049	0.094	-0.022	-0.077	-0.070	0.002	-0.036
DR1	0.207	0.222	0.267	0.132	0.104	0.126	0.184	0.178
DR2	0.307	0.318	0.190	0.201	0.190	0.208	0.244	0.223
LCIP	0.235	0.285	0.090	0.038	0.284	0.291	0.240	0.300
LCIN	-0.072	-0.025	0.036	-0.044	-0.003	-0.009	0.033	0.007
UNIT1	0.284	0.246	0.153	0.264	0.207	0.218	0.176	0.206
UNIT2	0.372	0.334	0.133	0.397	0.225	0.259	0.211	0.252
UNIT3	0.234	0.228	0.000	0.282	0.252	0.274	0.170	0.247
UNIT4	0.353	0.314	0.021	0.437	0.254	0.277	0.178	0.252
FINAL	0.475	0.438	0.203	0.466	0.415	0.446	0.320	0.443

FACTOR THEORY CORRELATION MATRIX FOR MALES

VARIATE	EFMP	EFMN	CR1	CR2	PSVR	GEFT2	GEFT3	HPT1
HSPC	0.221	0.165	0.006	0.045	-0.029	0.019	0.042	-0.015
HSCA	0.228	0.095	0.150	0.201	-0.001	0.109	0.109	0.174
HSPS	0.205	0.161	0.196	0.213	0.068	0.030	0.083	0.152
QSAT	0.213	0.048	0.182	0.252	0.258	0.276	0.310	-0.033
ALG	0.250	0.052	0.036	0.122	0.091	0.105	0.153	-0.082
TRIG	0.341	0.218	0.097	0.159	0.107	0.073	0.127	0.137
SMDP	0.097	0.067	-0.051	-0.052	-0.254	-0.180	-0.126	-0.064
SMDN	0.323	0.306	0.056	0.072	-0.032	-0.006	0.011	0.087
PUMP	0.620	0.554	0.102	0.206	0.014	0.087	0.062	0.126
PUMN	0.616	0.572	0.174	0.253	0.152	0.131	0.094	0.141
RQMA	0.303	0.170	-0.032	0.041	0.074	0.185	0.167	-0.082
RQPS	0.216	0.147	0.193	0.263	0.057	0.156	0.215	0.030
AIKP	0.668	0.703	0.066	0.111	0.071	-0.074	0.004	0.024
AIKN	0.684	0.722	0.093	0.146	0.115	-0.004	0.088	-0.024
CLMP	0.548	0.527	0.104	0.175	0.139	0.139	0.157	0.126
CLMN	0.641	0.652	0.111	0.160	0.176	0.048	0.135	-0.071
EFMP	0.704	0.743	0.075	0.147	-0.063	-0.050	0.042	0.141
EFMN	0.743	0.893	0.084	0.119	-0.069	-0.151	-0.033	0.131
CR1	0.075	0.084	0.420	0.393	0.475	0.347	0.331	0.332
CR2	0.147	0.119	0.393	0.417	0.380	0.419	0.429	0.395
PSVR	-0.063	-0.069	0.475	0.380	0.851	0.428	0.327	0.115
GEFT2	-0.050	-0.151	0.347	0.419	0.428	0.749	0.764	0.330
GEFT3	0.042	-0.033	0.331	0.429	0.327	0.764	0.887	0.270
HPT1	0.141	0.131	0.332	0.395	0.115	0.330	0.270	0.978
HPT2	0.029	0.010	0.189	0.252	0.039	0.298	0.305	0.603
VSAT	-0.126	-0.214	-0.009	0.017	0.001	0.106	0.113	-0.050
NS1	0.104	0.058	-0.022	-0.002	0.074	0.006	-0.023	-0.068
NS2	-0.089	-0.173	0.035	0.069	0.099	0.222	0.212	0.075
DR1	0.046	-0.091	0.122	0.152	0.278	0.262	0.210	0.011
DR2	0.161	0.075	0.156	0.198	0.216	0.212	0.170	0.180
LCIP	0.228	0.250	0.135	0.098	0.298	-0.034	-0.091	0.049
LCIN	-0.063	-0.084	0.182	0.162	0.284	0.210	0.170	0.179
UNIT1	0.222	0.160	0.010	0.077	-0.123	0.031	0.090	0.012
UNIT2	0.239	0.168	0.059	0.135	-0.054	0.088	0.147	0.018
UNIT3	0.275	0.305	0.122	0.157	-0.020	0.027	0.122	0.094
UNIT4	0.311	0.288	0.104	0.169	-0.110	0.005	0.103	0.099
FINAL	0.403	0.325	0.068	0.145	-0.041	0.005	0.100	-0.053

FACTOR THEORY CORRELATION MATRIX FOR MALES

VARIATE	HPT2	VSAT	NS1	NS2	DR1	DR2	LCIP	LCIN
HSPC	-0.021	0.005	0.057	0.001	0.091	0.087	0.032	-0.010
HSCA	0.086	0.032	0.006	-0.027	0.130	0.139	-0.106	0.067
HSPS	0.096	0.002	0.010	-0.080	0.039	0.101	-0.068	0.088
QSAT	0.002	0.142	0.183	0.115	0.339	0.297	0.132	0.078
ALG	-0.027	0.169	0.222	0.142	0.347	0.287	0.173	0.025
TRIG	0.090	0.073	0.148	0.110	0.250	0.235	0.217	0.063
SMDP	-0.101	0.039	-0.148	-0.010	-0.054	-0.106	0.006	-0.161
SMDN	-0.024	-0.037	-0.045	0.018	0.060	0.038	0.171	-0.072
PUMP	-0.016	-0.049	0.192	-0.049	0.207	0.307	0.235	-0.072
PUMN	-0.014	-0.072	0.193	-0.049	0.222	0.318	0.285	-0.025
ROMA	-0.056	0.018	0.156	0.094	0.267	0.190	0.090	0.036
ROPS	0.011	0.096	0.080	-0.022	0.132	0.201	0.038	-0.044
AIKP	-0.031	-0.125	0.179	-0.077	0.104	0.190	0.284	-0.003
AIKN	-0.053	-0.116	0.191	-0.070	0.126	0.208	0.291	-0.009
CLMP	0.043	-0.080	0.178	0.002	0.184	0.244	0.240	0.033
CLMN	-0.079	-0.085	0.196	-0.036	0.178	0.223	0.300	0.007
EFMP	0.029	-0.126	0.104	-0.089	0.046	0.161	0.228	-0.063
EFMN	0.010	-0.214	0.058	-0.173	-0.091	0.075	0.250	-0.084
CR1	0.189	-0.009	-0.022	0.035	0.122	0.156	0.135	0.182
CR2	0.252	0.017	-0.002	0.069	0.152	0.198	0.098	0.162
PSVR	0.039	0.001	0.074	0.099	0.278	0.216	0.298	0.284
GEFT2	0.298	0.106	0.006	0.222	0.262	0.212	-0.034	0.210
GEFT3	0.305	0.113	-0.023	0.212	0.210	0.170	-0.091	0.170
HPT1	0.603	-0.050	-0.068	0.075	0.011	0.180	0.049	0.179
HPT2	0.423	0.006	-0.055	0.090	0.007	0.096	-0.047	0.123
VSAT	0.006	0.110	0.018	0.087	0.097	0.041	-0.056	0.008
NS1	-0.055	0.018	0.128	0.032	0.129	0.119	0.122	0.007
NS2	0.090	0.087	0.032	0.138	0.140	0.081	0.004	0.064
DR1	0.007	0.097	0.129	0.140	0.292	0.215	0.134	0.096
DR2	0.096	0.041	0.119	0.081	0.215	0.225	0.153	0.080
LCIP	-0.047	-0.056	0.122	0.004	0.134	0.153	0.347	0.048
LCIN	0.123	0.008	0.007	0.064	0.096	0.080	0.048	0.147
UNIT1	0.016	0.031	0.043	-0.022	0.057	0.087	-0.054	-0.037
UNIT2	0.019	0.057	0.082	-0.004	0.107	0.147	0.002	-0.036
UNIT3	0.060	-0.025	0.005	-0.067	-0.021	0.061	0.020	-0.017
UNIT4	0.057	0.022	0.024	-0.063	0.016	0.104	-0.003	-0.056
FINAL	-0.042	0.055	0.127	-0.018	0.150	0.189	0.103	-0.055

FACTOR THEORY CORRELATION MATRIX FOR MALES

VARIATE	UNIT1	UNIT2	UNIT3	UNIT4	FINAL
HSPC	0.139	0.133	0.085	0.130	0.200
HSCA	0.308	0.262	0.187	0.301	0.320
HSPS	0.273	0.259	0.265	0.342	0.339
QSAT	0.240	0.337	0.175	0.285	0.462
ALG	0.238	0.322	0.139	0.271	0.508
TRIG	0.165	0.198	0.138	0.208	0.384
SMDP	0.001	-0.036	-0.002	0.081	0.053
SMDN	0.005	-0.017	0.017	0.045	0.081
PUMP	0.284	0.372	0.234	0.353	0.475
PUMN	0.246	0.334	0.228	0.314	0.438
RQMA	0.153	0.133	0.000	0.021	0.203
RQPS	0.264	0.397	0.282	0.437	0.466
AIKP	0.207	0.225	0.252	0.254	0.415
AIKN	0.218	0.259	0.274	0.277	0.446
CLMP	0.176	0.211	0.170	0.178	0.320
CLMN	0.206	0.252	0.247	0.252	0.443
EFMP	0.222	0.239	0.275	0.311	0.403
EFMN	0.160	0.168	0.305	0.288	0.325
CR1	0.010	0.059	0.122	0.104	0.068
CR2	0.077	0.135	0.157	0.169	0.145
PSVR	-0.123	-0.054	-0.020	-0.110	-0.041
GEFT2	0.031	0.088	0.027	0.005	0.005
GEFT3	0.090	0.147	0.122	0.103	0.100
HPT1	0.012	0.018	0.094	0.099	-0.053
HPT2	0.016	0.019	0.060	0.057	-0.042
VSAT	0.031	0.057	-0.025	0.022	0.055
NS1	0.043	0.082	0.005	0.024	0.127
NS2	-0.022	-0.004	-0.067	-0.063	-0.018
DR1	0.057	0.107	-0.021	0.016	0.150
DR2	0.087	0.147	0.061	0.104	0.189
LCTP	-0.054	0.002	0.020	-0.003	0.103
LCTN	-0.037	-0.036	-0.017	-0.056	-0.055
UNIT1	0.220	0.232	0.166	0.253	0.290
UNIT2	0.232	0.292	0.198	0.303	0.359
UNIT3	0.166	0.198	0.233	0.279	0.270
UNIT4	0.253	0.303	0.279	0.393	0.397
FINAL	0.290	0.359	0.270	0.397	0.520

Table 22. Matrices of factor-scoring coefficients

FACTOR-SCORING COEFFICIENTS FOR FEMALES

VARIATE	AE	PCP	PAMF	PUM	FAP	ALM	SA	FI/FD	FC
HSPC	0.352	-0.097	0.017	-0.145	-0.023	0.068	0.081	0.031	0.008
HSCA	0.568	-0.157	0.028	-0.234	-0.037	0.109	0.130	0.051	0.013
HSPS	0.475	-0.131	0.023	-0.196	-0.031	0.091	0.109	0.042	0.011
QSAT	0.000	0.378	-0.005	-0.095	-0.127	0.048	-0.128	0.114	0.012
ALG	0.000	0.634	-0.008	-0.160	-0.213	0.081	-0.214	0.191	0.020
TRIG	0.000	0.322	-0.004	-0.081	-0.108	0.041	-0.109	0.097	0.010
SMDP	0.000	0.000	-0.945	0.080	-0.091	-0.261	-0.052	0.104	0.020
SMDN	0.000	0.000	1.165	-0.099	0.112	0.322	0.064	-0.128	-0.025
PUMP	0.000	0.000	0.000	1.040	-0.253	0.175	0.067	-0.270	0.015
PUMN	0.000	0.000	0.000	0.137	-0.033	0.023	0.009	-0.036	0.002
ROMA	0.000	0.000	0.000	0.000	0.207	0.033	0.021	-0.046	0.018
ROPS	0.000	0.000	0.000	0.000	1.046	0.168	0.108	-0.232	0.089
AIKP	0.000	0.000	0.000	0.000	0.000	-1.002	0.063	0.267	-0.005
AIKN	0.000	0.000	0.000	0.000	0.000	-0.253	0.016	0.068	-0.001
CLMP	0.000	0.000	0.000	0.000	0.000	0.198	-0.012	-0.053	0.001
CLMN	0.000	0.000	0.000	0.000	0.000	0.329	-0.021	-0.088	0.002
EFMP	0.000	0.000	0.000	0.000	0.000	0.019	-0.001	-0.005	0.000
EFMN	0.000	0.000	0.000	0.000	0.000	-0.398	0.025	0.106	-0.002
CR1	0.000	0.000	0.000	0.000	0.000	0.000	0.723	0.139	0.301
CR2	0.000	0.000	0.000	0.000	0.000	0.000	0.393	0.075	0.164
PSVR	0.000	0.000	0.000	0.000	0.000	0.000	0.050	0.009	0.021
GEFT2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.891	0.158
GEFT3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.321	0.057
HPT1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.519
HPT2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.714
VSAT	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
NS1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
NS2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
DR1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
DR2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LCIP	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LCIN	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
UNIT1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
UNIT2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
UNIT3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
UNIT4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
FINAL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

FACTOR-SCORING COEFFICIENTS FOR MALES

VARIATE	AE	PCP	PAMF	PUM	FAP	ALM	SA	FI/FD	FC
HSPC	0.068	-0.034	0.008	-0.015	-0.007	-0.004	0.000	0.000	0.018
HSCA	0.652	-0.330	0.075	-0.143	-0.070	-0.039	0.002	-0.003	0.170
HSPS	0.593	-0.300	0.068	-0.130	-0.064	-0.036	0.002	-0.003	0.155
OSAT	0.000	0.441	-0.018	-0.156	-0.001	-0.046	0.079	-0.085	-0.118
ALG	0.000	0.570	-0.024	-0.201	-0.002	-0.059	0.102	-0.110	-0.152
TRIG	0.000	0.417	-0.017	-0.147	-0.001	-0.043	0.075	-0.081	-0.111
SMDP	0.000	0.000	0.770	-0.097	0.006	-0.028	-0.146	0.030	0.055
SMDN	0.000	0.000	0.358	-0.045	0.003	-0.013	-0.068	0.014	0.026
PUMP	0.000	0.000	0.000	0.649	-0.060	-0.460	0.070	-0.078	0.116
PUMN	0.000	0.000	0.000	0.548	-0.051	-0.389	0.059	-0.066	0.098
RQMA	0.000	0.000	0.000	0.000	-0.818	-0.132	-0.044	-0.032	-0.034
RQPS	0.000	0.000	0.000	0.000	0.977	0.158	0.053	0.039	0.041
AIKP	0.000	0.000	0.000	0.000	0.000	0.295	-0.019	0.061	-0.015
AIKN	0.000	0.000	0.000	0.000	0.000	0.423	-0.027	0.087	-0.022
CLMP	0.000	0.000	0.000	0.000	0.000	-0.564	0.036	-0.116	0.029
CLMN	0.000	0.000	0.000	0.000	0.000	0.426	-0.027	0.088	-0.022
EFMP	0.000	0.000	0.000	0.000	0.000	0.165	-0.010	0.034	-0.008
EFMN	0.000	0.000	0.000	0.000	0.000	0.662	-0.042	0.136	-0.034
CR1	0.000	0.000	0.000	0.000	0.000	0.000	-0.366	-0.198	0.056
CR2	0.000	0.000	0.000	0.000	0.000	0.000	-0.104	-0.056	0.016
PSVR	0.000	0.000	0.000	0.000	0.000	0.000	-0.868	-0.469	0.134
GEFT2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.541	0.123
GEFT3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.807	0.184
HPT1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-1.278
HPT2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.247
VSAT	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
NS1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
NS2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
DR1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
DR2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LCIP	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LCIN	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
UNIT1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
UNIT2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
UNIT3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
UNIT4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
FINAL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Figures 1-6: Reduced path diagrams for factors AE, PCP, and FAP

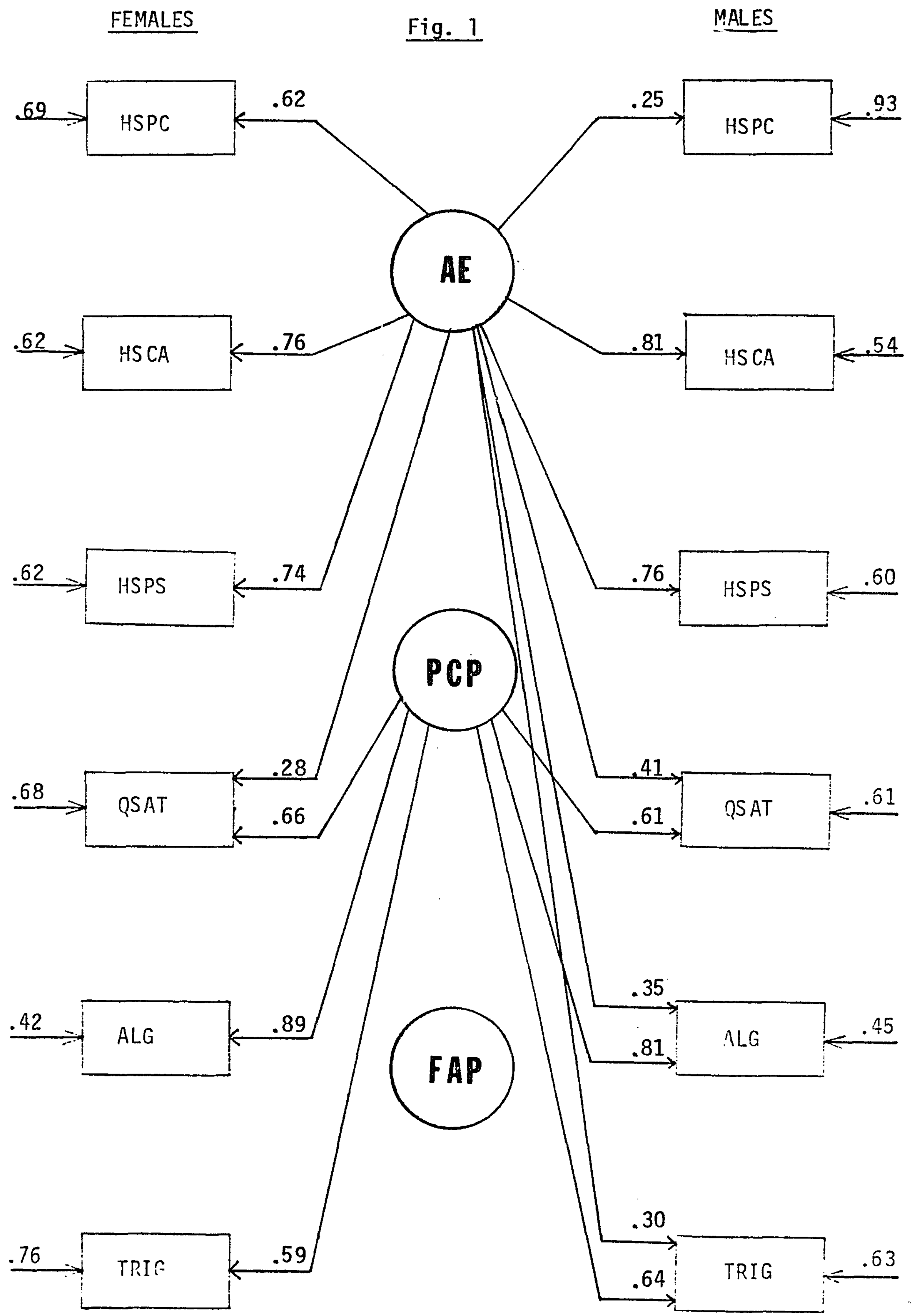


Fig. 2

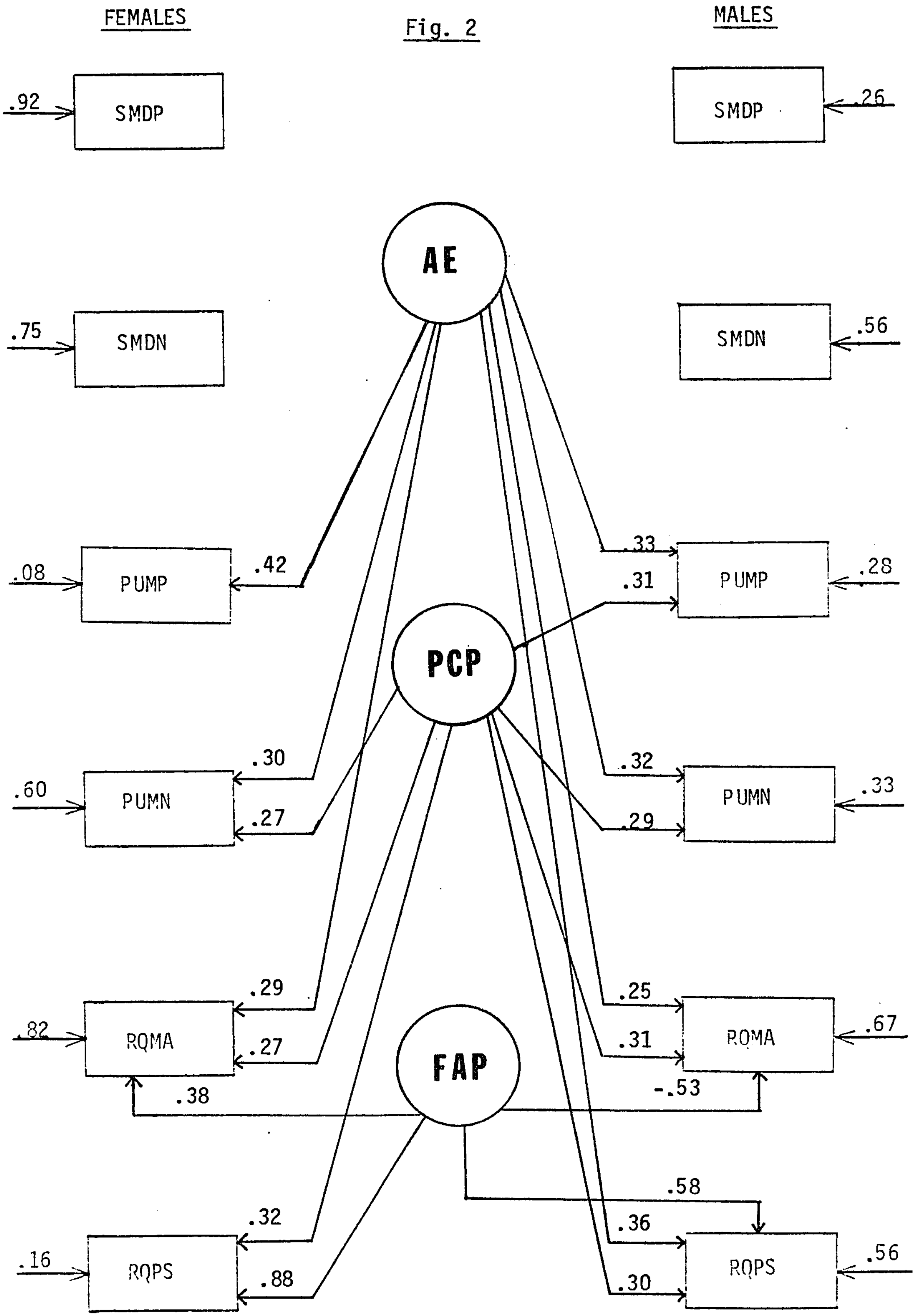

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Fig. 3

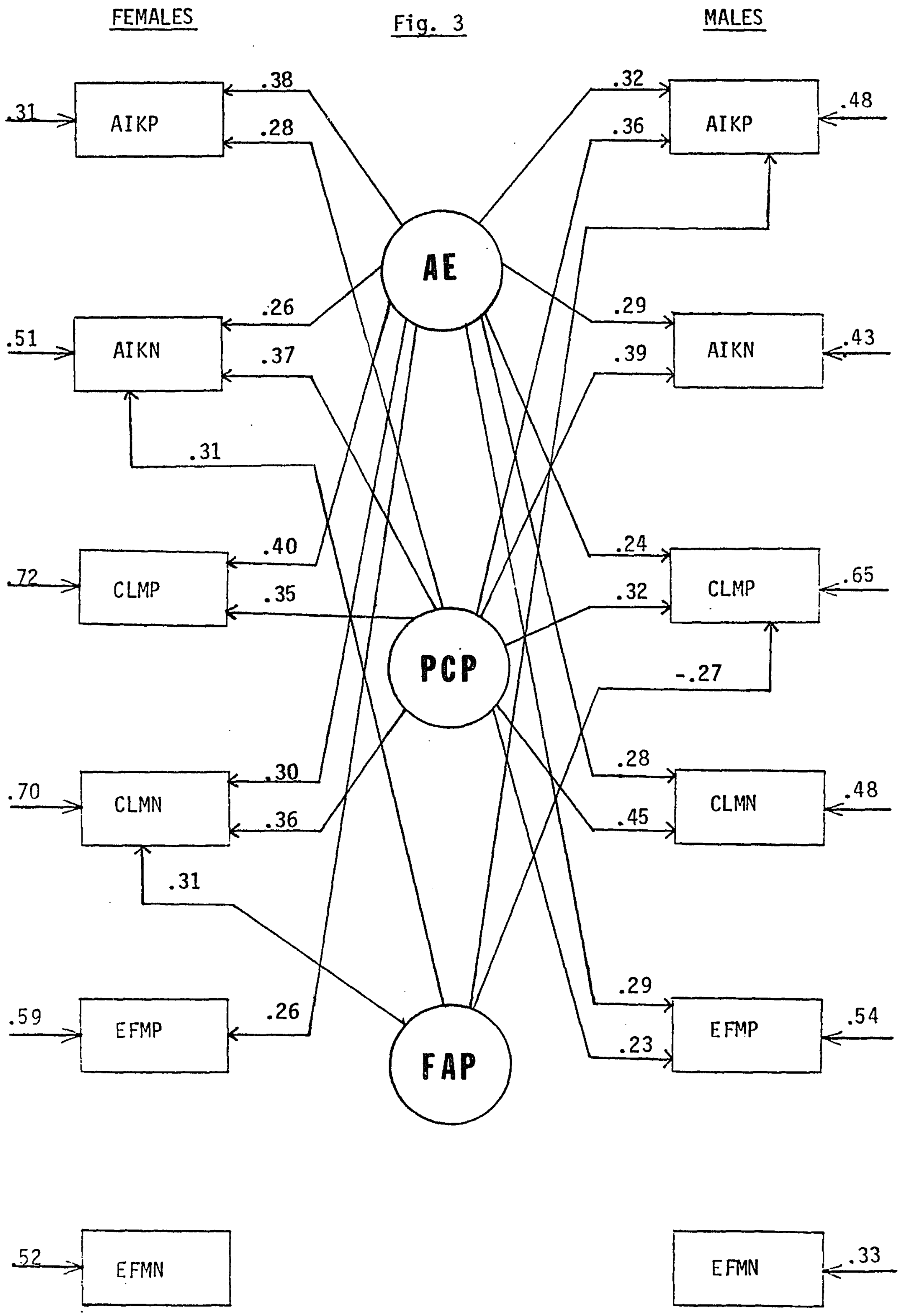
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Fig. 4

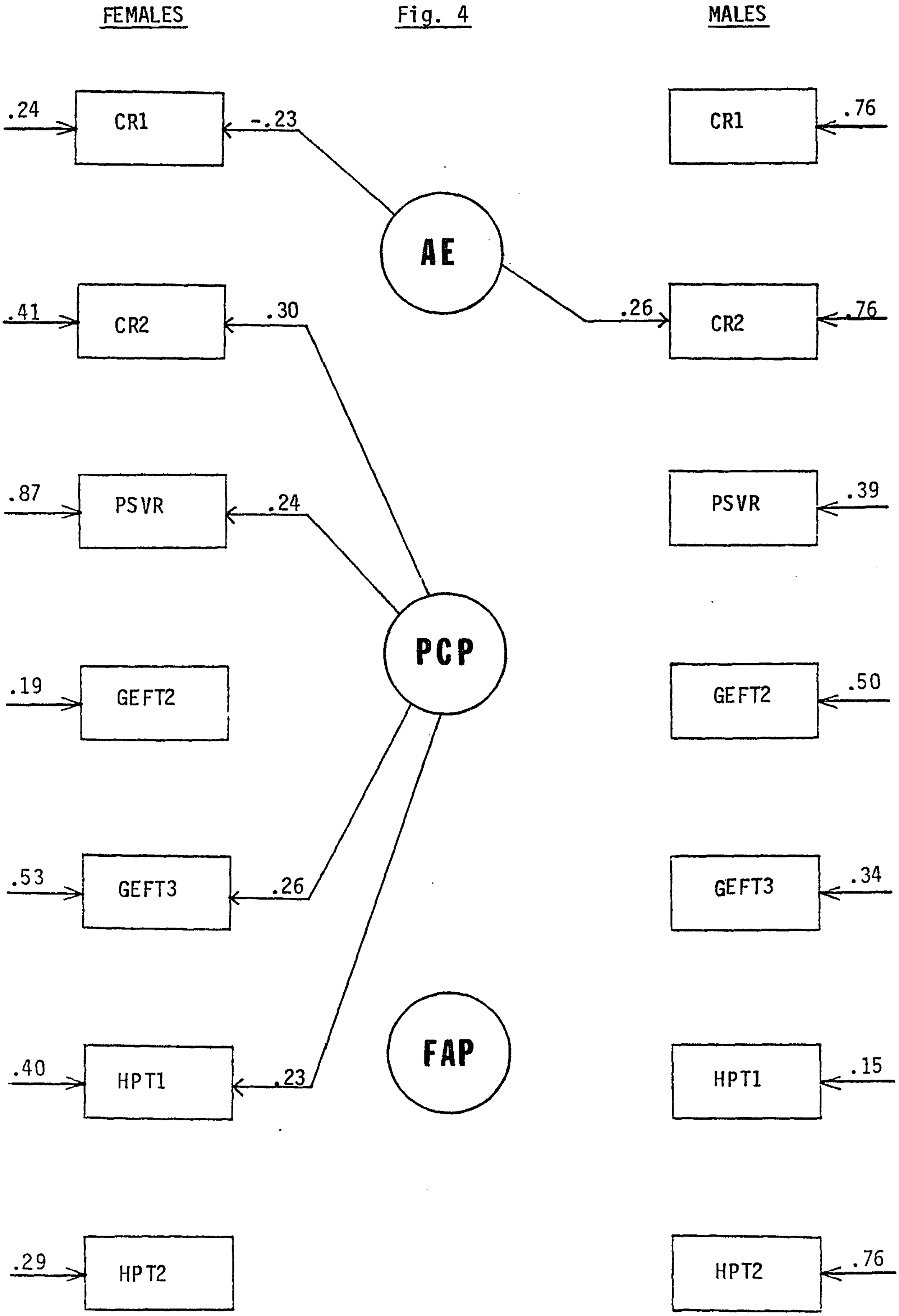
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Fig. 5

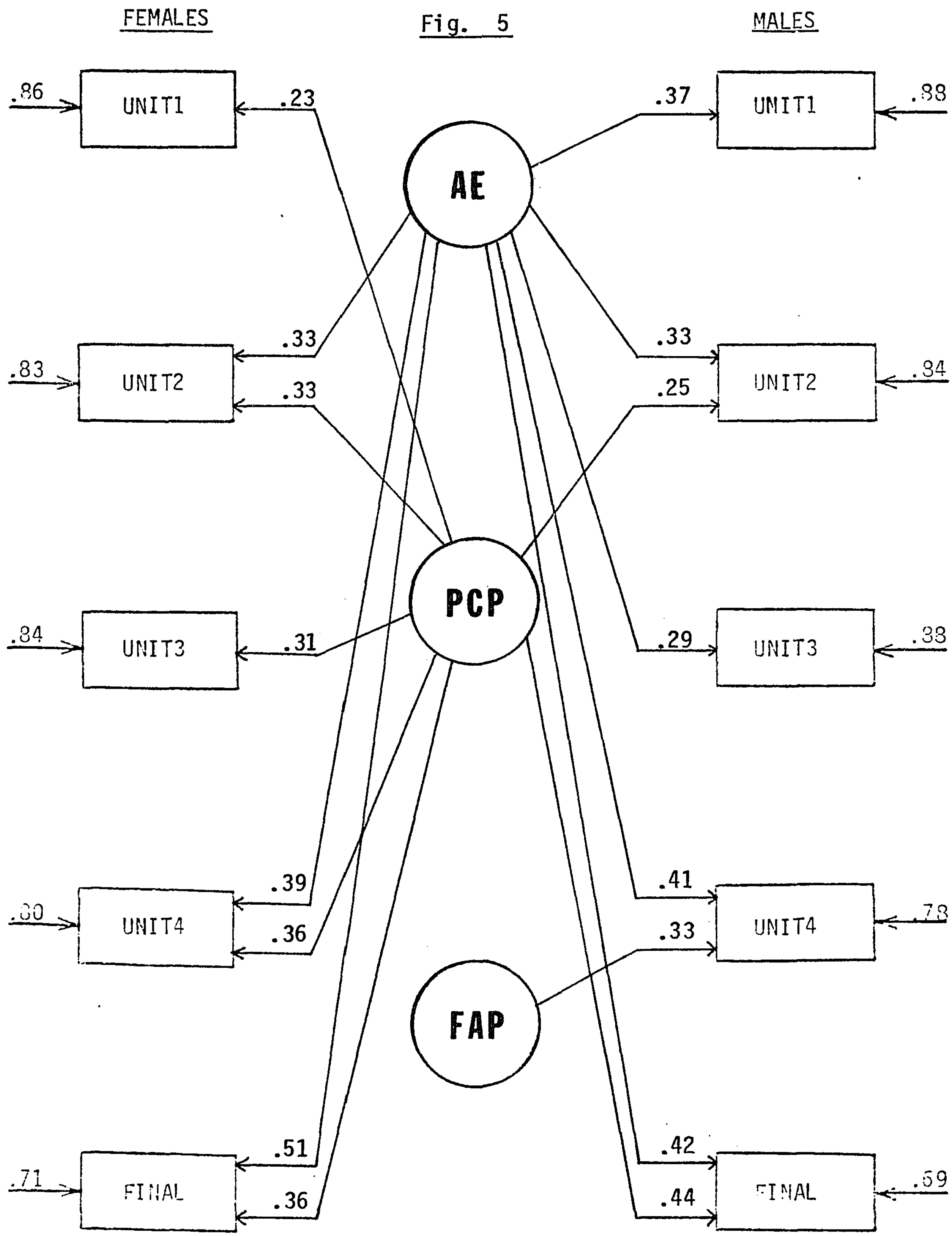
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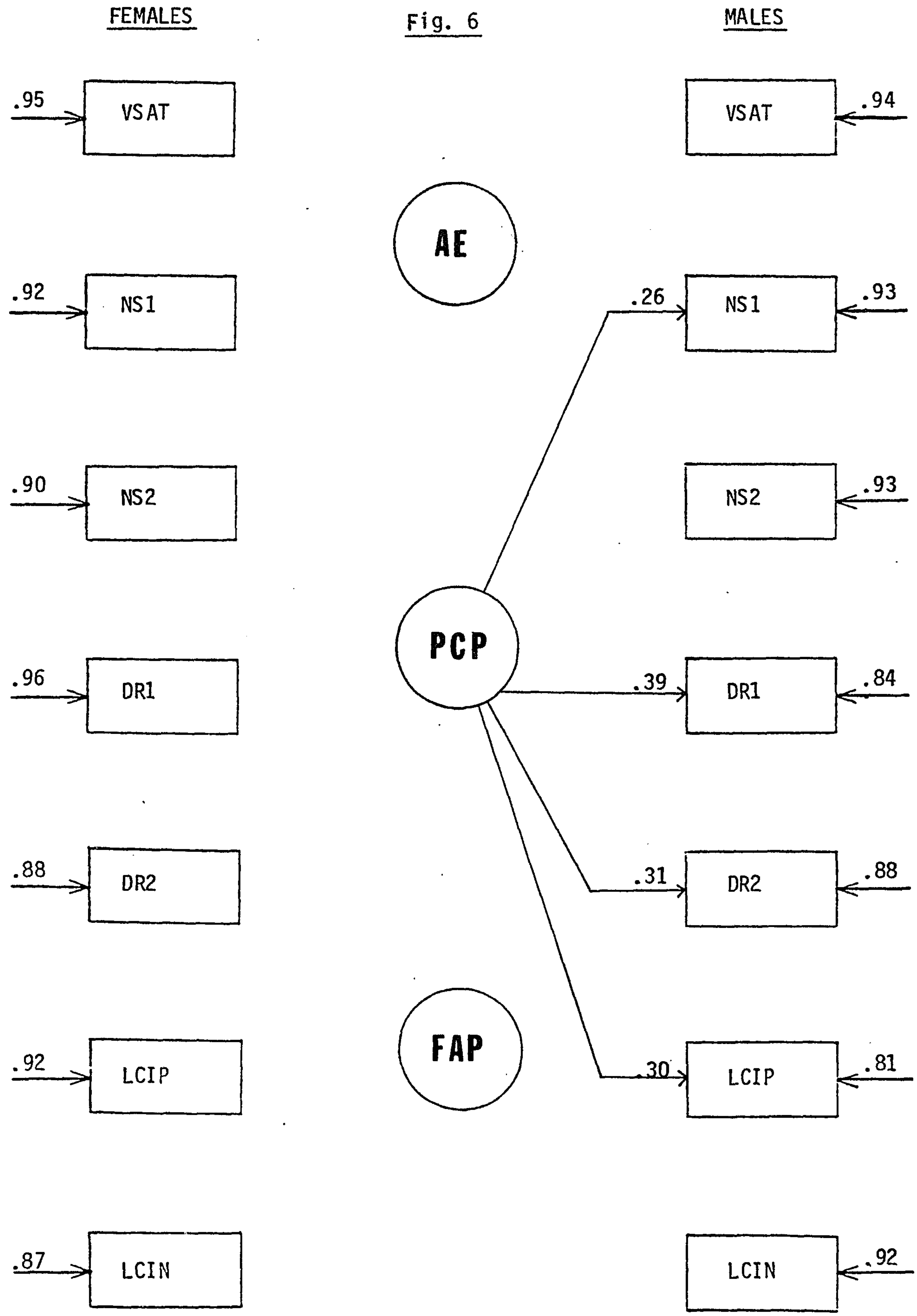
Fig. 6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Figures 7-12: Reduced path diagrams for factors PAMF, PUM, and ALM

Fig. 7

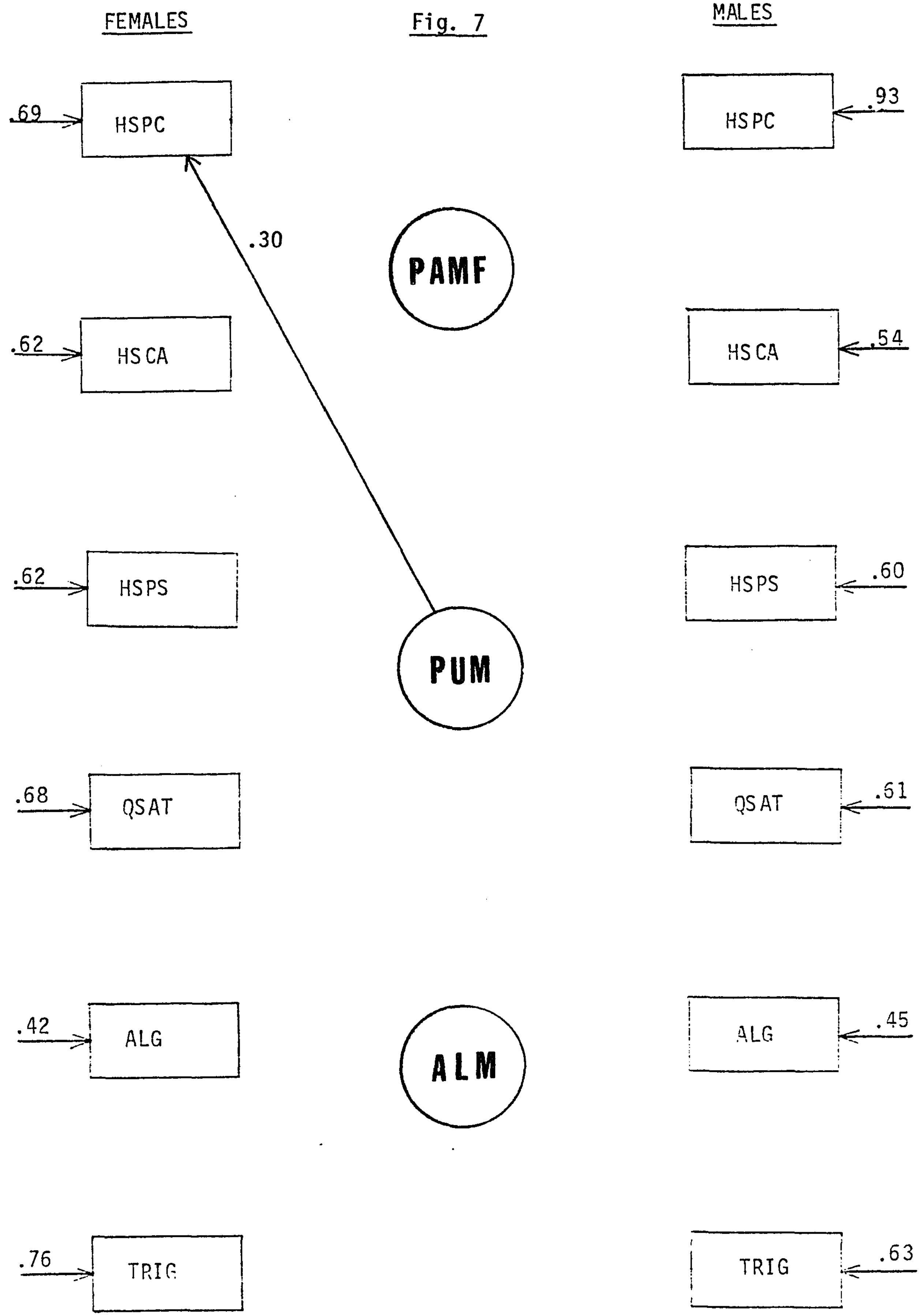

Fig. 8

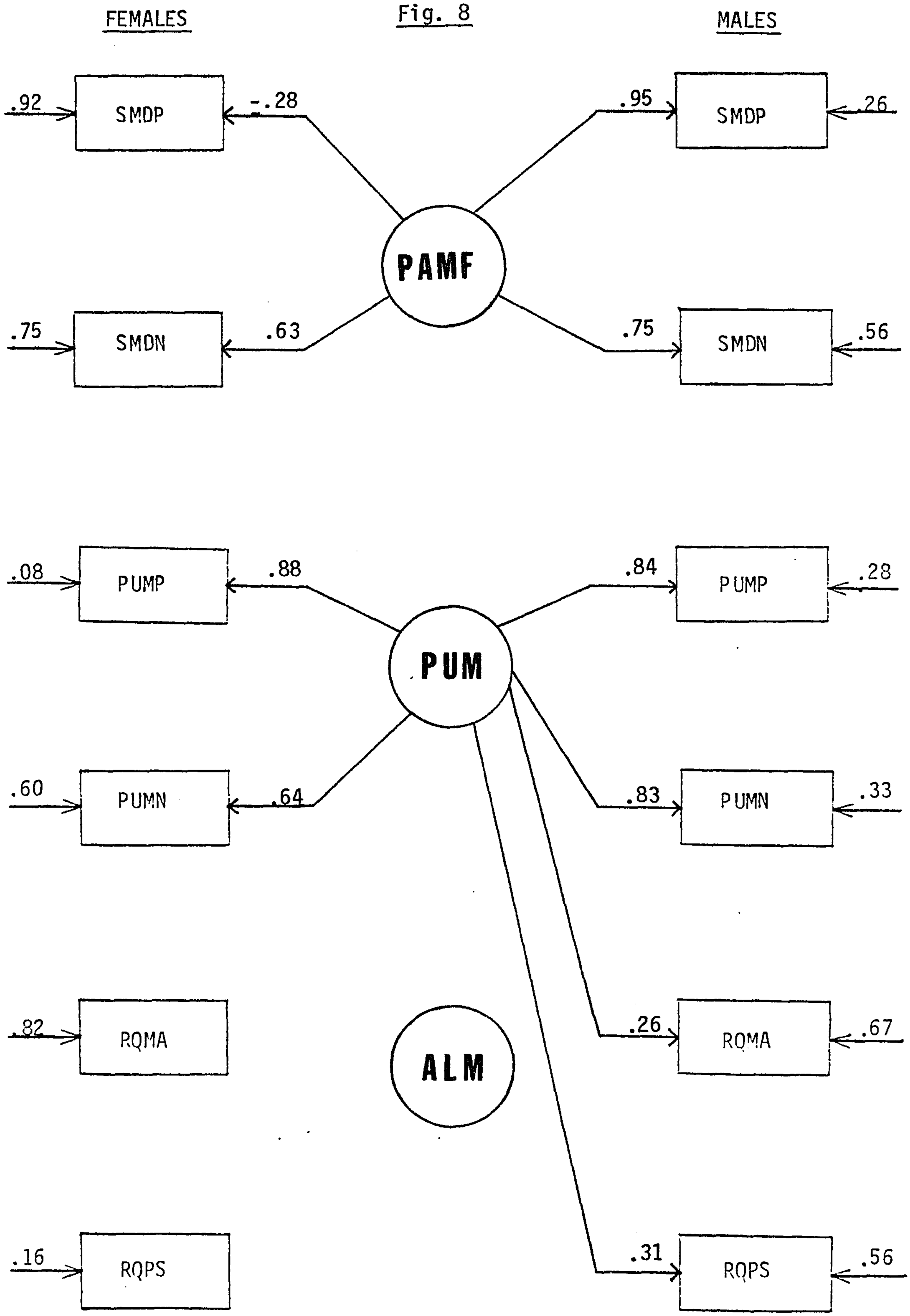
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Fig. 9

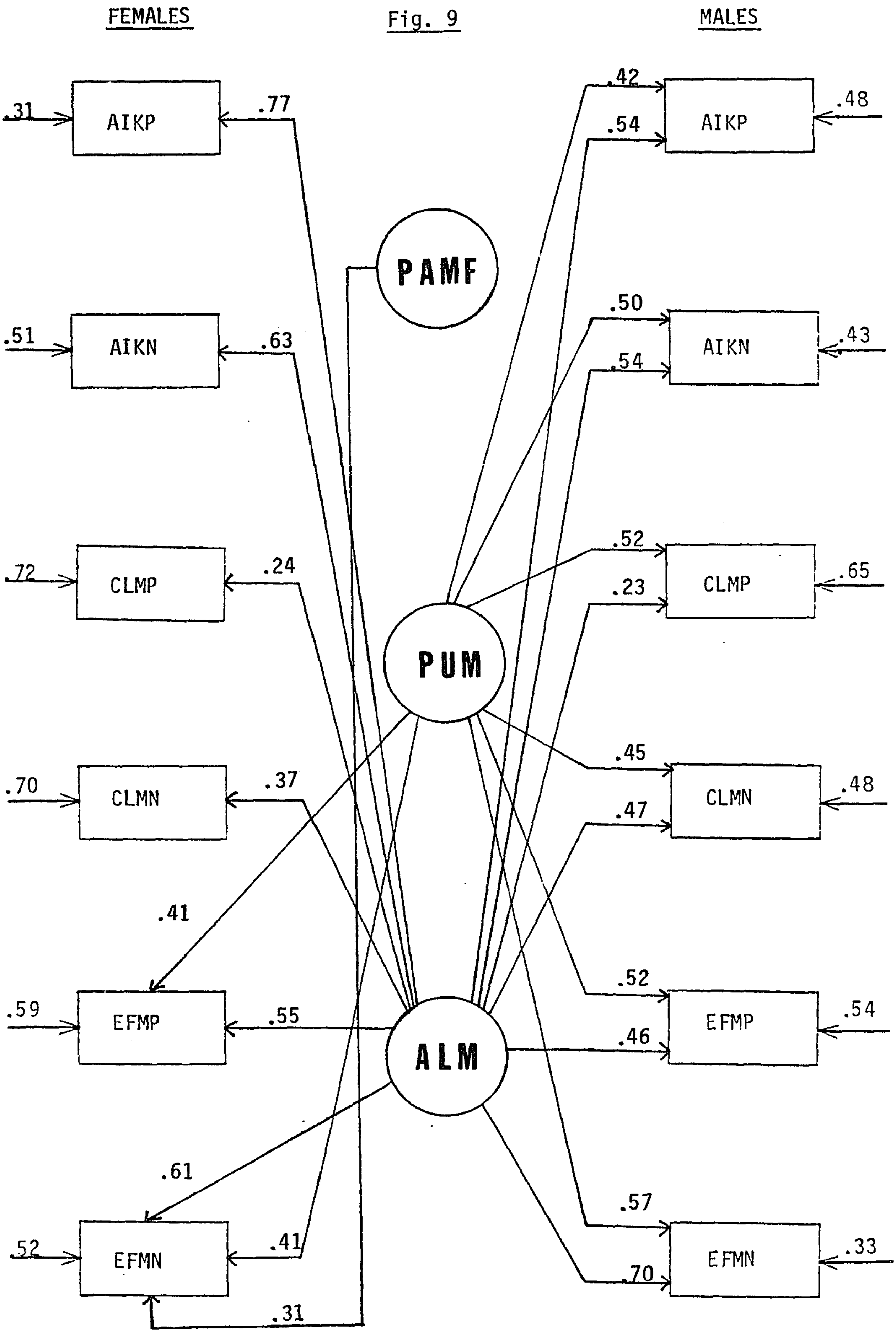
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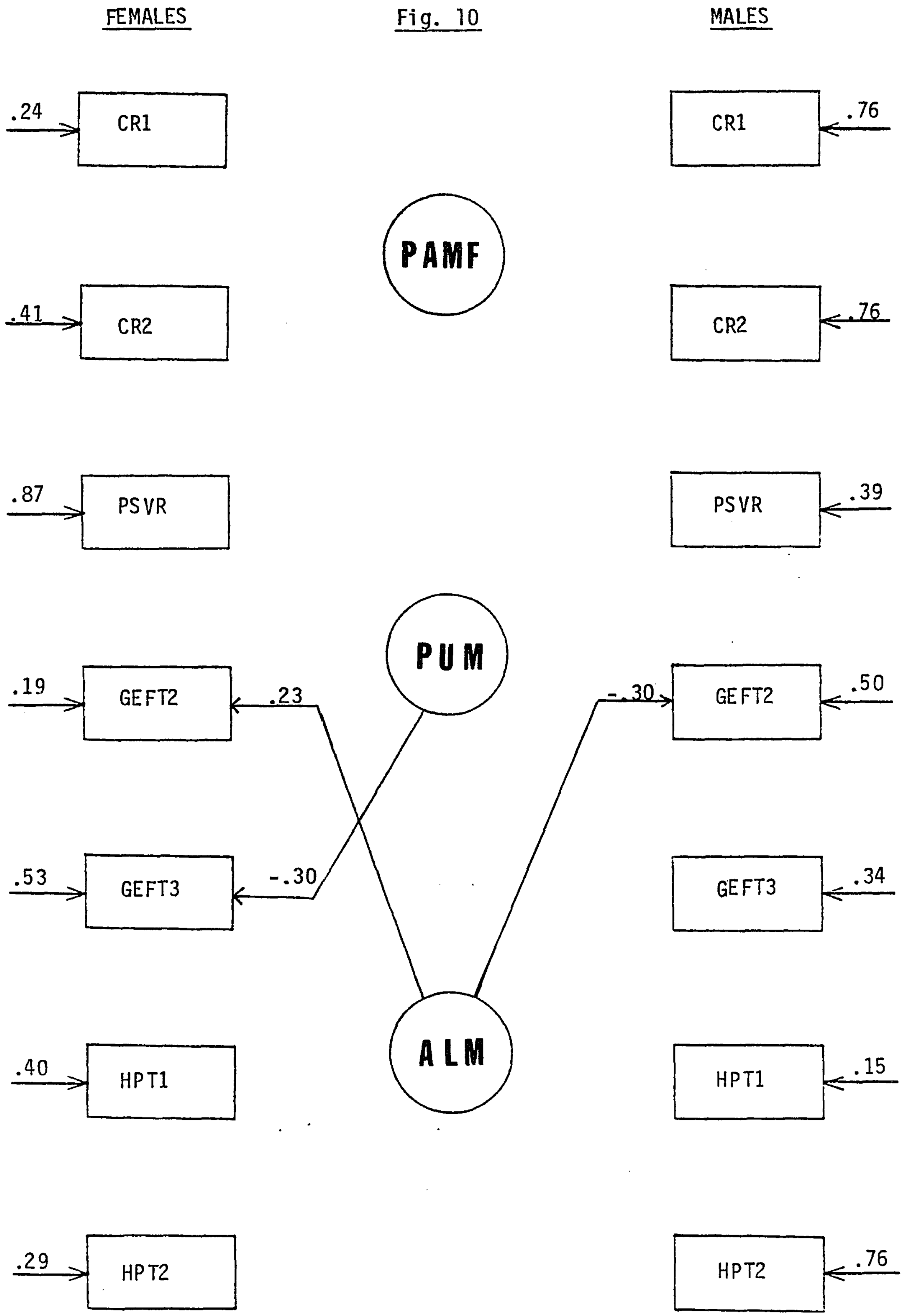
Fig. 10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HPT1
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HPT2
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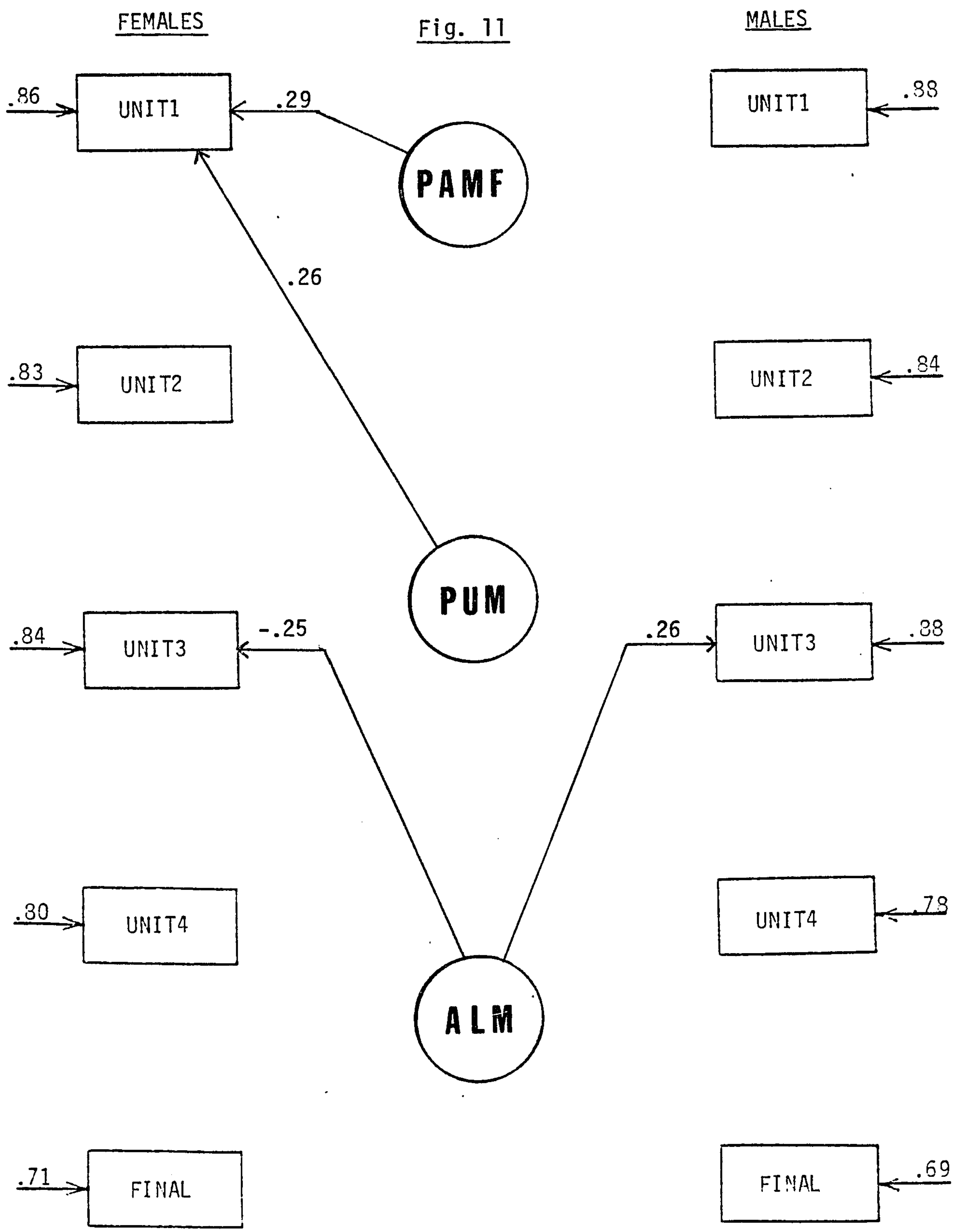
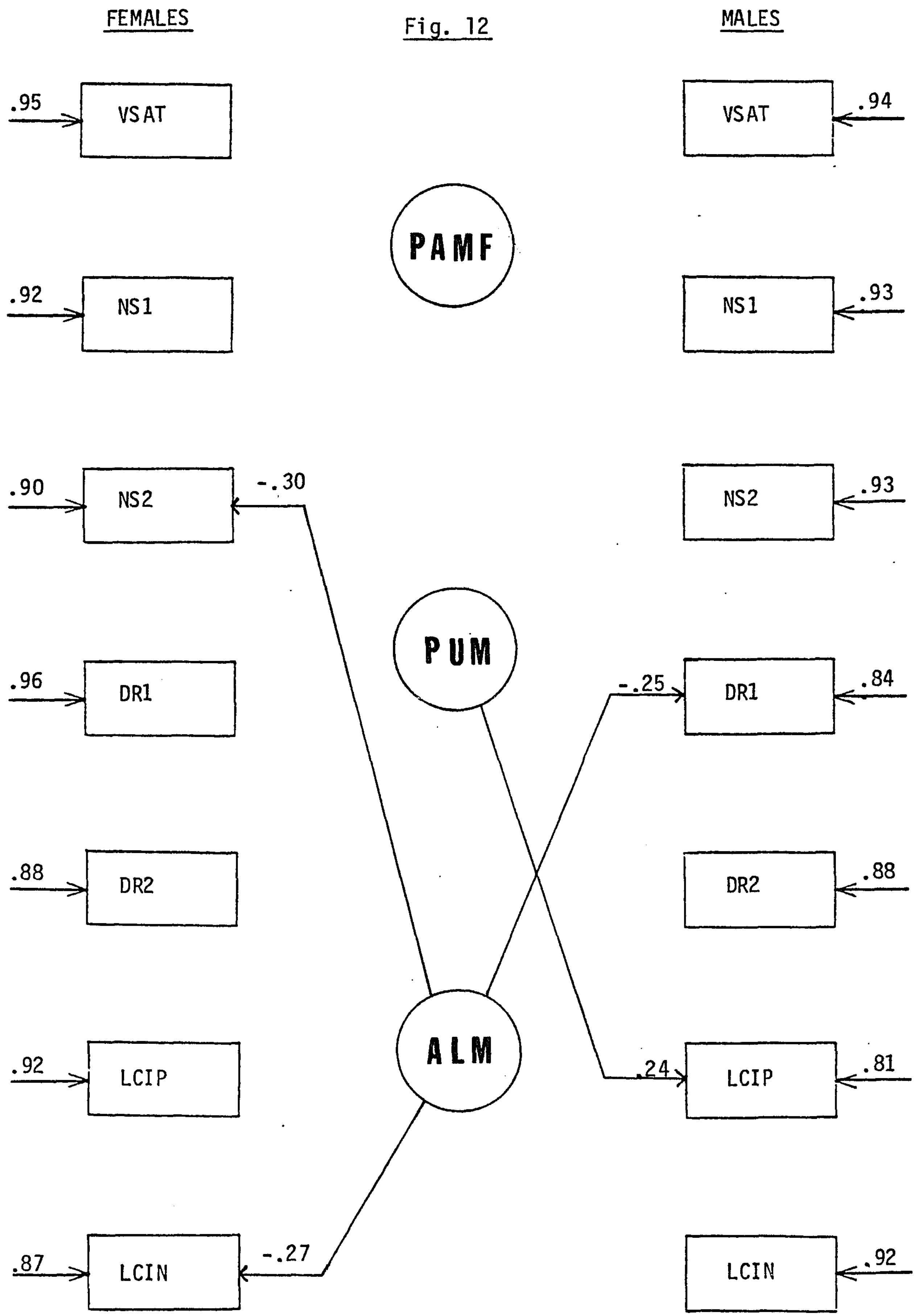
HPT2

Fig. 11



FEMALES
MALES
.86
UNIT1
.29
PAMF
UNIT1
.88
.26
.83
UNIT2
UNIT2
.84
PUM
.84
UNIT3
-.25
.26
UNIT3
.88
.80
UNIT4
UNIT4
.78
ALM
.71
FINAL
FINAL
.69


FEMALES
Fig. 12
MALES
.95
VSAT
.94
VSAT
PAMF
.92
NS1
.93
NS1
.90
NS2
-.30
.93
NS2
PUM
.96
DR1
-.25
DR1
.84
.88
DR2
DR2
.88
ALM
.92
LCIP
.24
LCIP
.81
.87
LCIN
-.27
LCIN
.92

Figures 13-18: Reduced path diagrams for factors SA, FI/FD, and FC

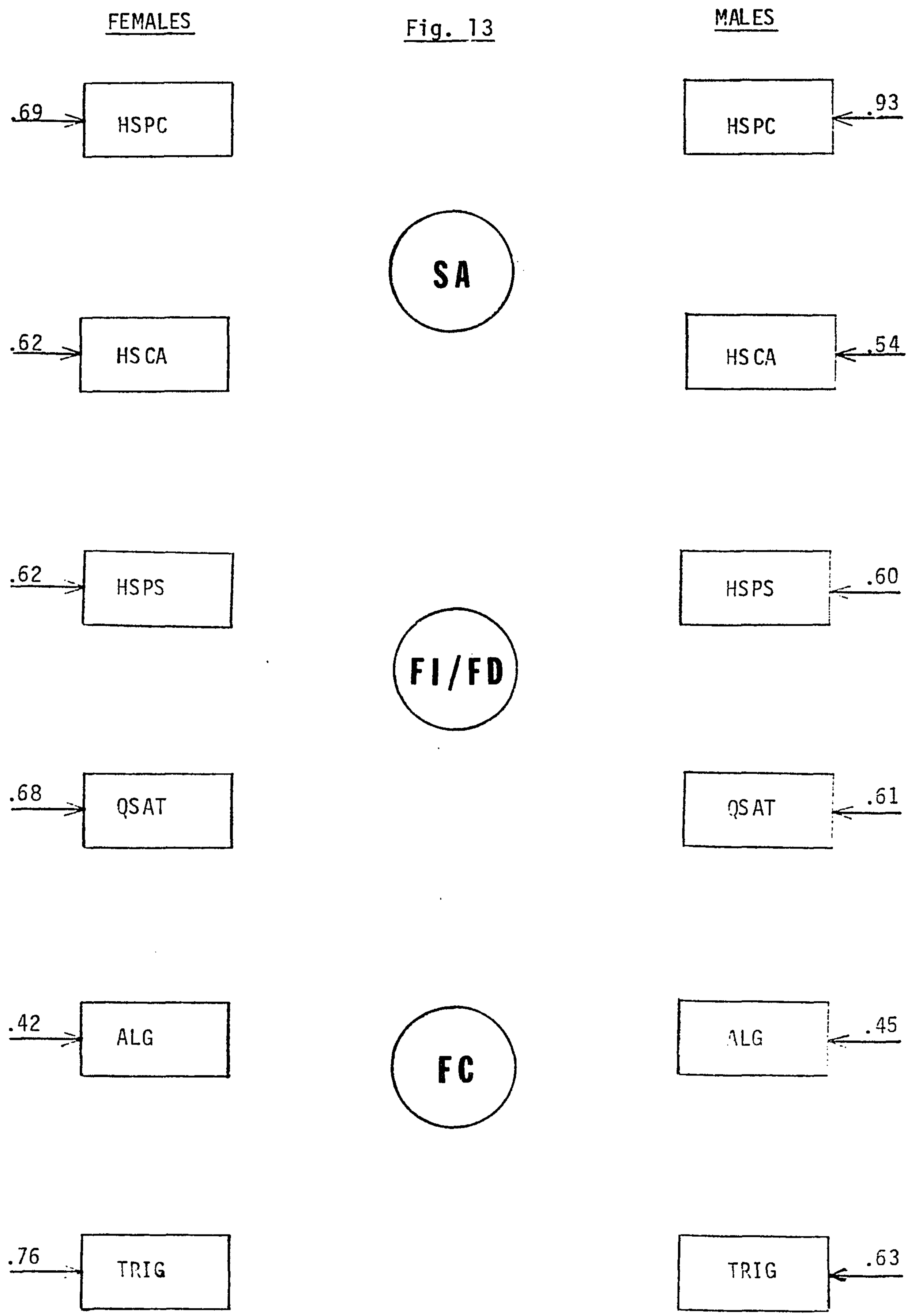


Fig. 14

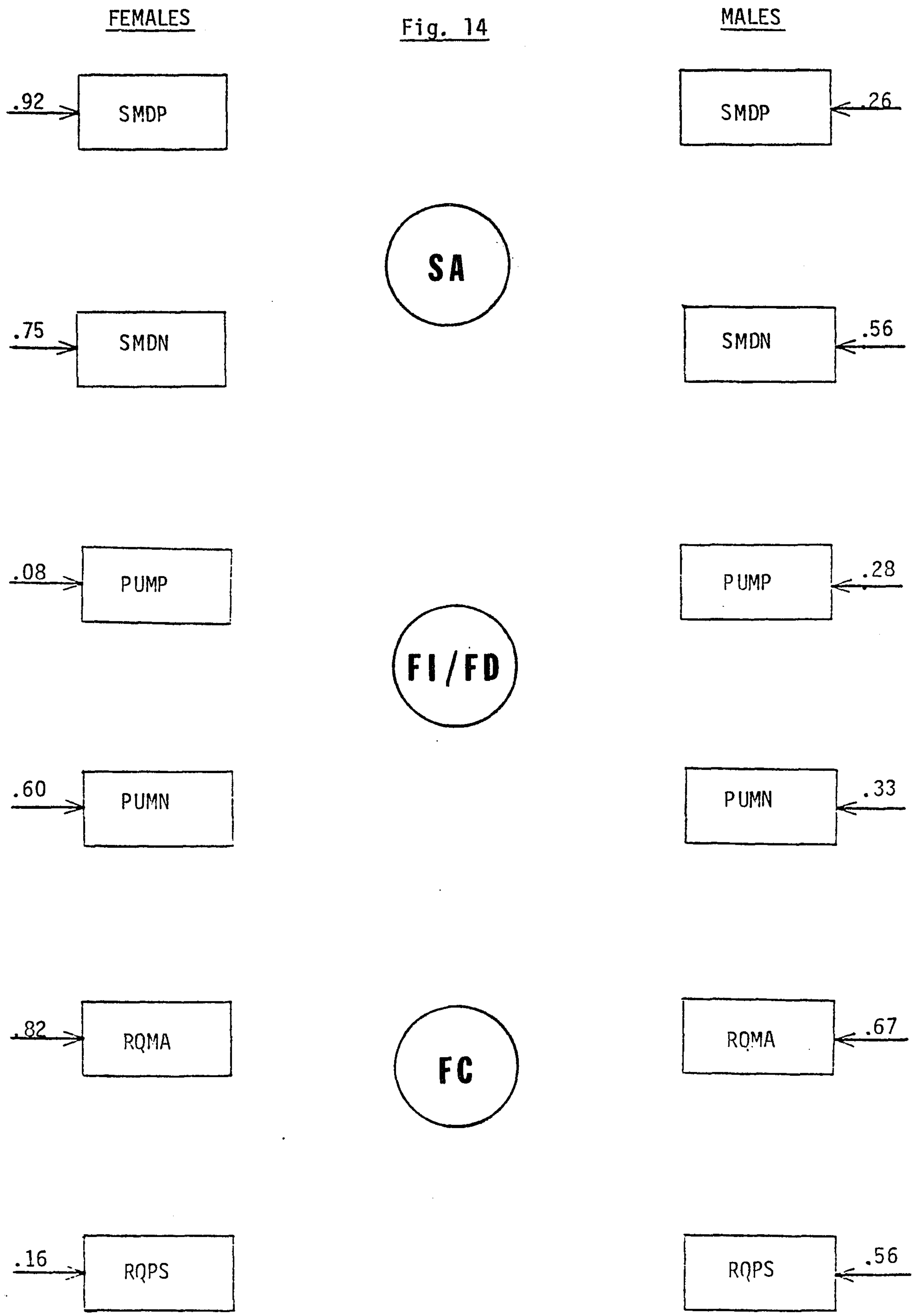
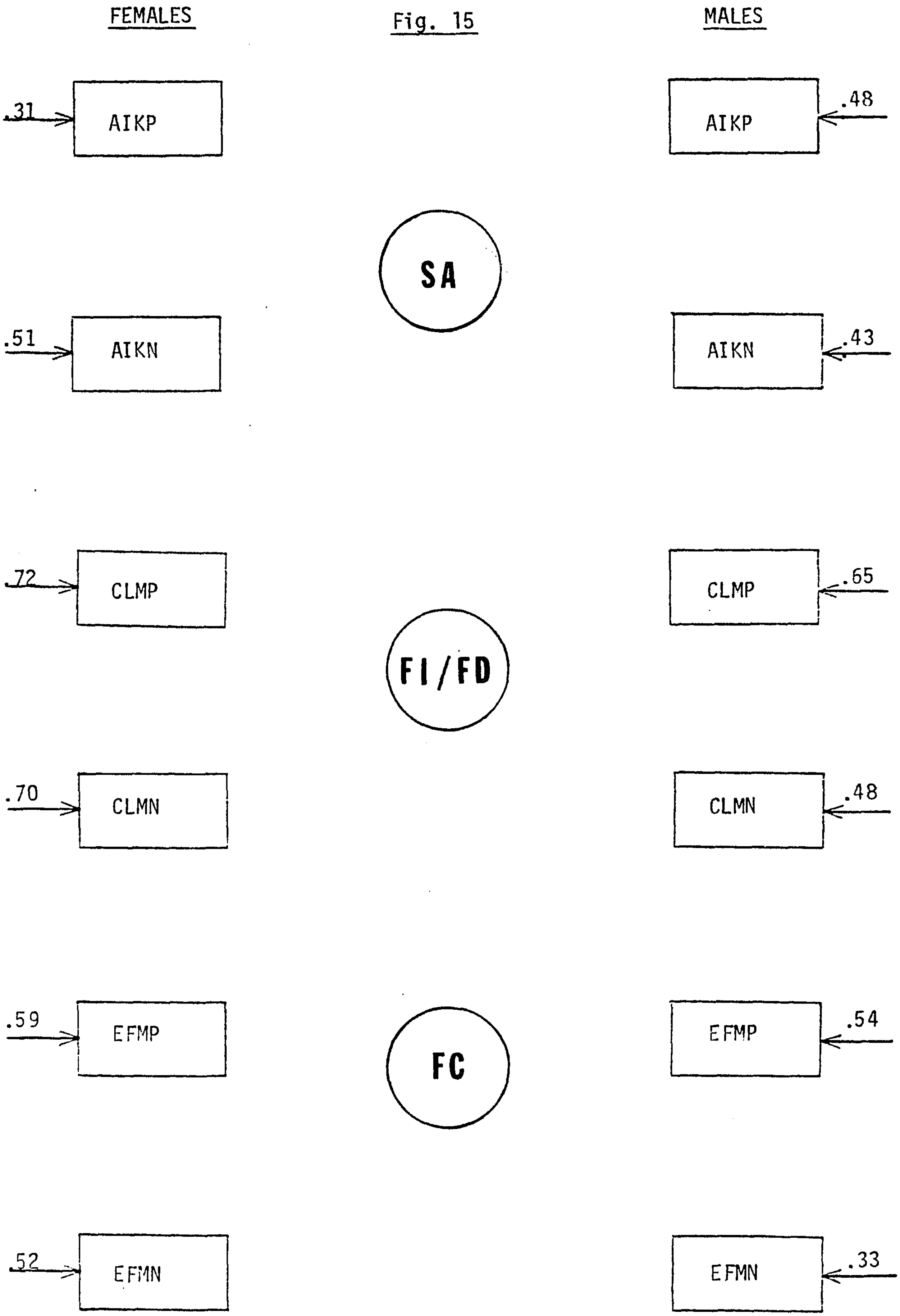

FEMALES
MALES
.92
SMDP
SMDP
.26
SA
.75
SMDN
SMDN
.56
.08
PUMP
PUMP
.28
FI/FD
.60
PUMN
PUMN
.33
.82
RQMA
RQMA
.67
FC
.16
RQPS
RQPS
.56

Fig. 15


FEMALES
MALES
.31
AIKP
AIKP
.48
SA
.51
AIKN
AIKN
.43
.72
CLMP
CLMP
.65
FI/FD
.70
CLMN
CLMN
.48
.59
EFMP
EFMP
.54
FC
.52
EFMN
EFMN
.33

FEMALES Fig. 16 MALES

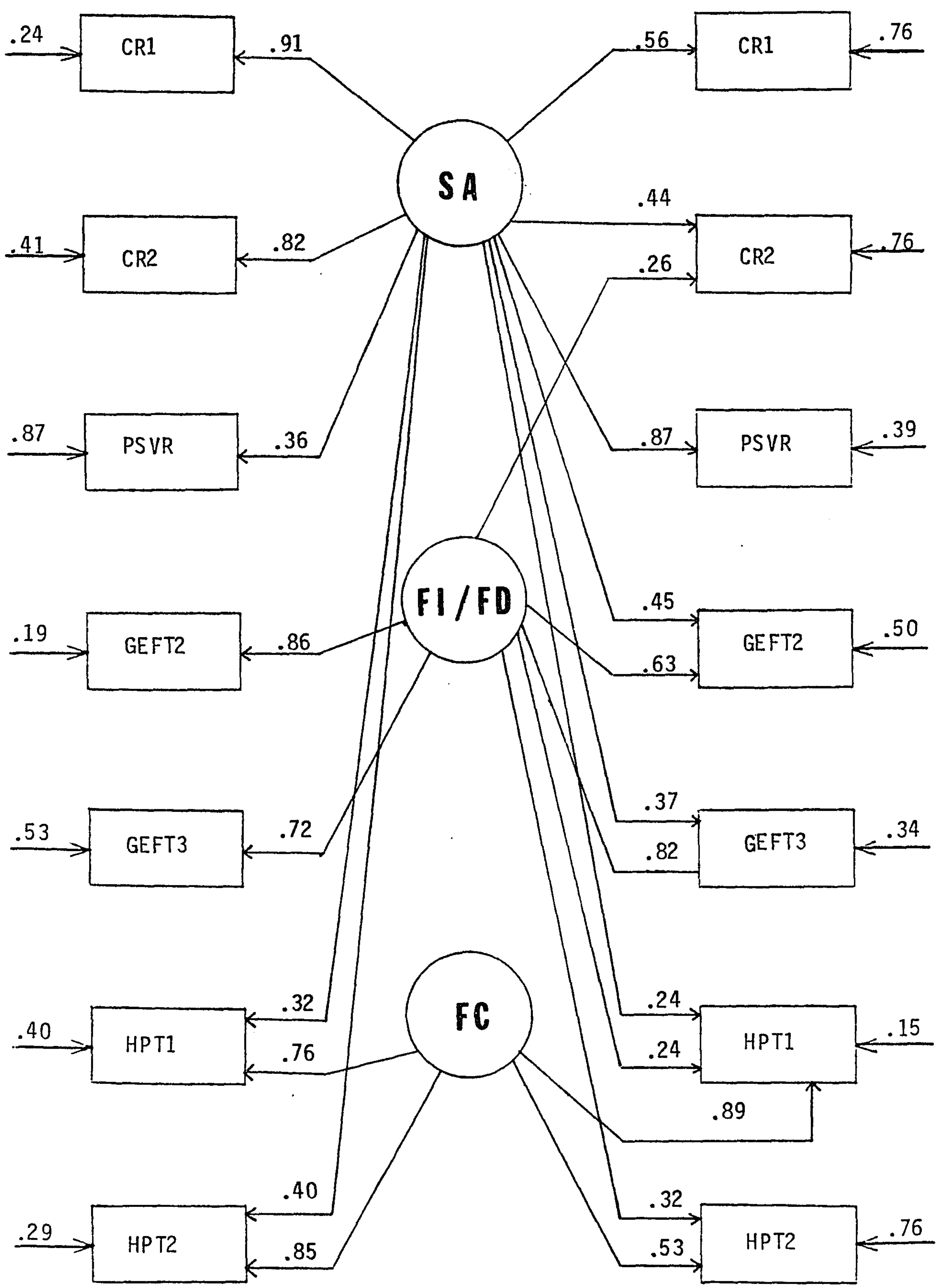
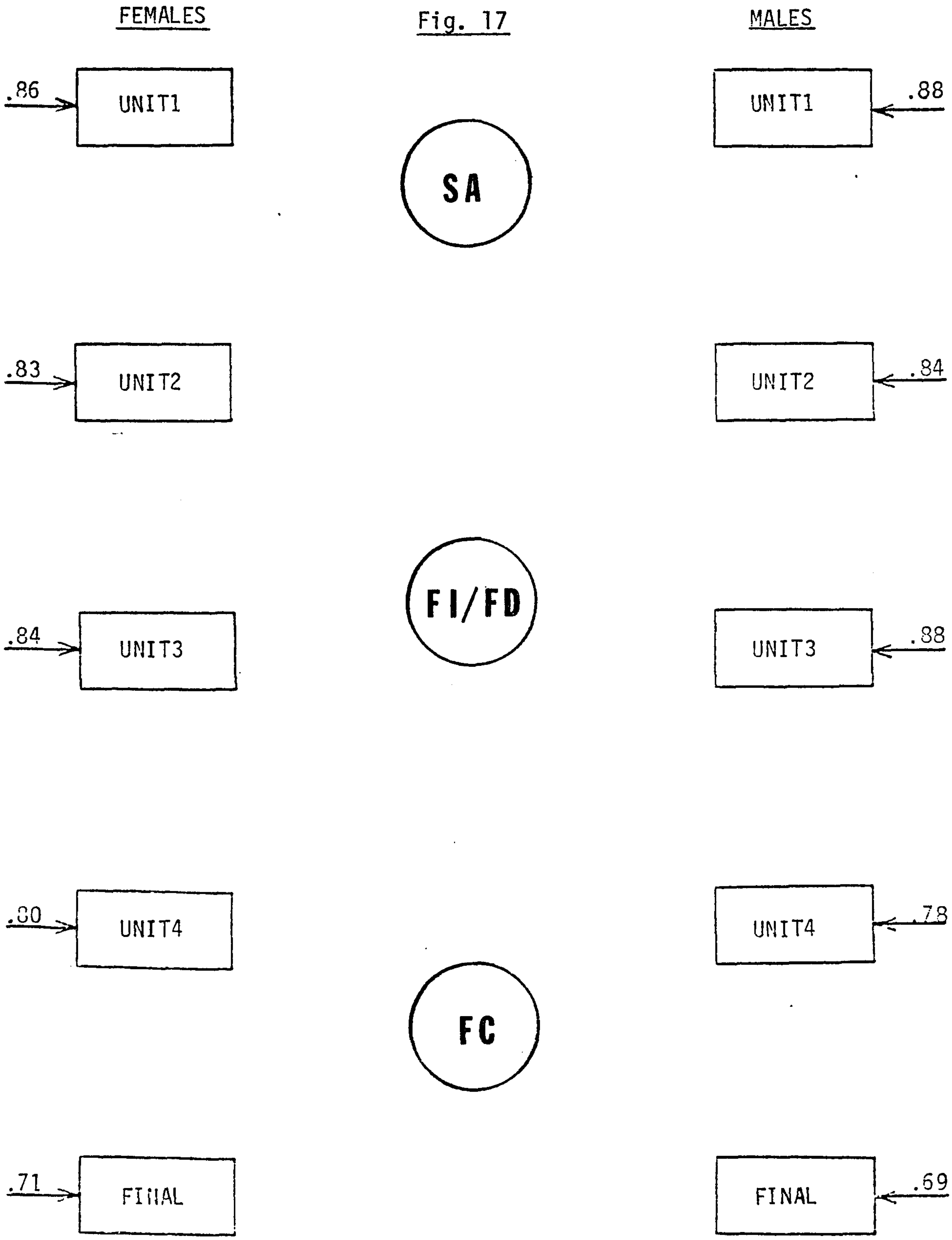
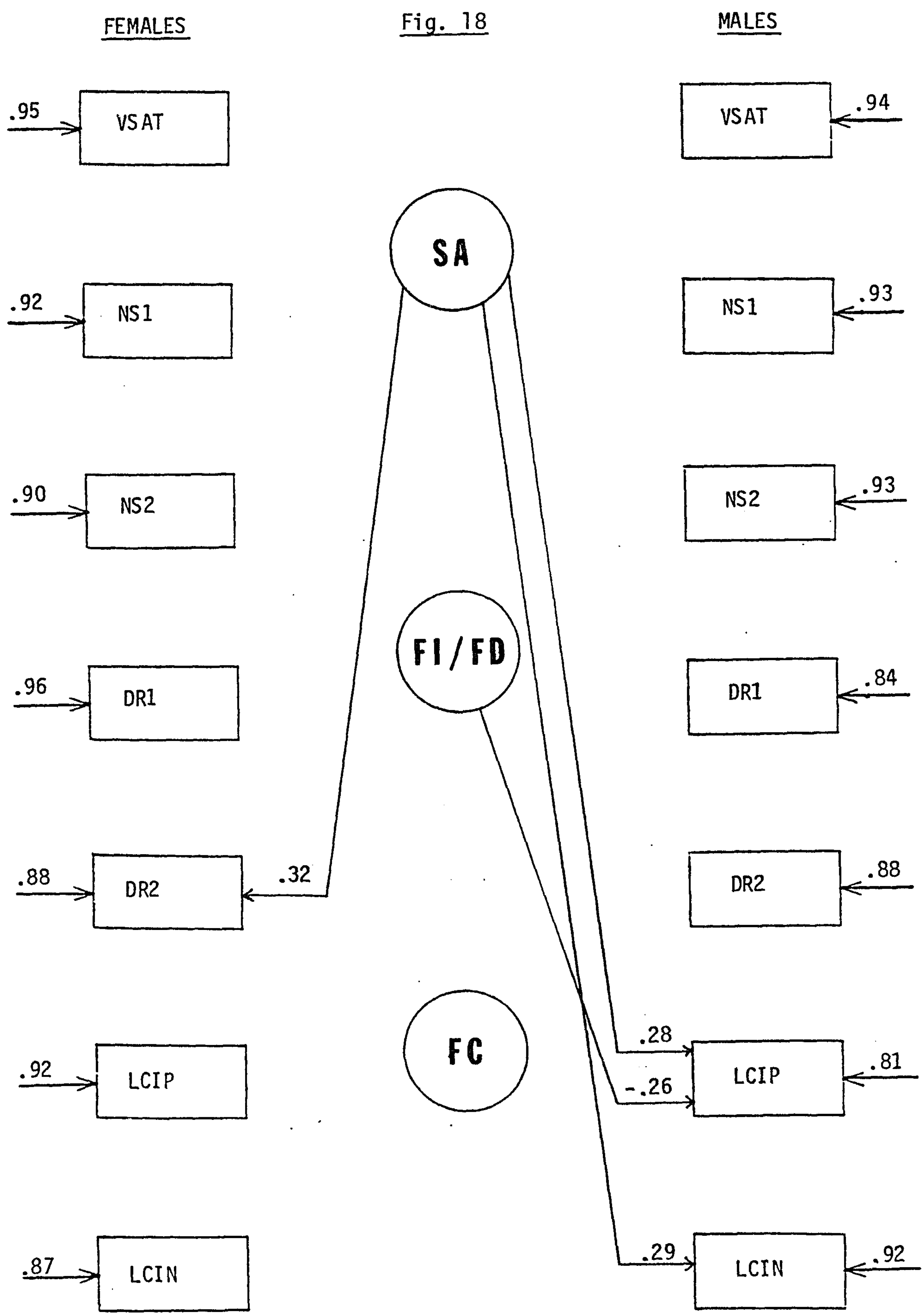


Fig. 17


FEMALES
MALES
.86
UNIT1
UNIT1
.88
SA
.83
UNIT2
UNIT2
.84
FI/FD
.84
UNIT3
UNIT3
.88
.80
UNIT4
UNIT4
.78
FC
.71
FINAL
FINAL
.69


FEMALES
Fig. 18
MALES
.95
VSAT
.94
VSAT
SA
.92
NS1
.93
NS1
.90
NS2
.93
NS2
FI/FD
.96
DR1
.84
DR1
.88
DR2
.32
.88
DR2
FC
.92
LCIP
.28
-.26
LCIP
.81
.87
LCIN
.29
LCIN
.92

Indications of goodness-of-fit for the models

In this final section we report the statistical evidence for the goodness-of-fit of the model for females and the model for males. The descriptive statistics of interest here are:

1) SSQ = sum of squared residual correlations
   = $\mathrm{ttr}(r_{ij}^2)$, where ttr is sum of entries above the main diagonal of the matrix of squared residuals
2) RMSQ = root mean square of the residual correlations
   = $\sqrt{2SSQ/(p(p+1))}$, where p is number of variates
3) principal components of the residual correlation matrix.

In Table 23 below, n denotes the number of factors, and we report the percentage of common variance accounted for in the residual correlation matrix by the first three principal components (abbreviated as P.C.).

Table 23. Goodness-of-fit information for the models

model	p	n	SSQ	RMSQ	% of common variance by P.C. 1	P.C. 2	P.C. 3
females	37	9	6.874	0.099	7.9%	7.2%	6.1%
males	37	9	5.032	0.085	7.3%	6.4%	5.5%

It is possible that after multiplication by an appropriate quantity (involving p, n, and N = the number in sample), SSQ might have approximately a chi-squared distribution. If we adjust the statistic of Lawley mentioned in Chapter II for the number of factors extracted, we obtain:

$$\chi^2 = (N - 1 - (2p - 2n + 5)/6)SSQ$$

where the number of degrees of freedom would be $(p - n)(p - n - 1)/2$. With N = 62 for females, this computation yields a value of 349.43. With N = 72 for males, this computation yields a value of 306.11. In both cases, we would have 378 degrees of freedom. We must emphasize that these values may not have a chi-squared distribution, since SSQ is computed from residual correlations instead of original correlations. However, even without knowledge of its distribution theory, SSQ and RMSQ provide a descriptive statistic of goodness-of-fit for our models. We can see that the model for males fits somewhat better than the model for females. Whether the fit is significantly better is a question which must await the development of a statistical test for goodness-of-fit of models fitted using FaM.

Perhaps more revealing is the evidence provided by the principal component analysis of the residual correlation matrix. Here we see that for both models, the first three principal components account for very little common variance in the residuals. This indicates that additional factors added to the model would accomplish little in explaining the covariances between the variates.

A closer inspection of these principal components revealed that the unit and final calculus exams loaded predominantly on the first principal component, while the verbal SAT score and the logical reasoning measures loaded predominantly on the second principal component for both males and females. Recall that these measures were not used as specifying variates for any factor. It is not surprising that components representing these measures might show up in the principal component analysis of the residual correlation matrix left after factor extraction.

The small leftover common variance shared by the unit and final calculus exams, as represented by the first principal component of the residuals, is most likely due to the simple fact that these were exams from a single course. Exploratory analysis indicated that the verbal and logical reasoning measures may not be appropriate measures to include in the models we were considering. We would not expect our models to explain the covariances among these variables very well. Thus, some of their common variance showed up in the second principal component of the residuals, which represent the covariances that our models did not explain.

In summary, there appears ample evidence that the sample data from the second subsample fits our developed models quite reasonably. With the structural parameters from these models for males and females in hand, we can now compare their structures. The conclusions and implications of this comparison of structural models are discussed in the next chapter.

CHAPTER VII

CONCLUSIONS AND IMPLICATIONS OF THE STUDY

We started out to develop covariance structural models for measures of mathematics achievement and participation and measures of related cognitive and affective variables at the level of college calculus. It was necessary to develop separate models for males and females because of the strong statistical evidence of sex-differences in covariance structure. In this final chapter, we divide our discussion into three parts:

1) comparison of structural models for males and females,
2) implications for educational policy,
3) implications for future research.

Comparision of Structural Models for Males and Females

In general, as could be expected, specifying variates loaded most heavily on the factors they specified. In terms of the criterion variate for the models, the calculus final exam, the two most important factors for both males and females were clearly academic experience and precalculus preparation. These two factors made substantial contributions to explaining the variances and covariances among the high school coursework measures, HSPC, HSCA, and HSPS, as well as the pretest measures ALG and TRIG and the quantitative SAT score.

The contributions of these two factors to the variances and covariances among the affective measures were more modest, while negligible contributions were made by them to explaining the variances and covariances among the cognitive measures. This was true for the models for both females and males.

Since these two factors were extracted first under the Factorial Modeling algorithm, one should remember that the contributions of all other factors in the models are with academic experience and precalculus preparation controlled. In particular, under these conditions, we found that the role future academic plans played in explaining variances and covariances among the variates was almost negligible for both sexes, except for the specifying variates RQMA and RQPS. This factor contributed slightly more to the variances and covariances among the unit exams and the final exam for males than females, and the loadings of the affective variates on this factor were quite modest for both males and females.

The most profound differences between males and females in terms of covariance structure were found in examination of the affective factors. Indeed, the exploratory analysis using the first subsample indicated that while a three-factor structure appeared adequate for both sexes, the nature of that structure seemed quite different for females and males. This was confirmed by our covariance structural models.

For females, each of the affective variates loaded quite distinctly on one of the three affective factors which we called perceived appropriateness of mathematics for females, perceived usefulness of mathematics, and attitude toward learning mathematics. The pattern of loadings adhered closely to the specification of variates for each factor. That is, SMDP and SMDN loaded most heavily on PAMF, PUMP and PUMN loaded most heavily on PUM, and the AIKP, AIKN, CLMP, CLMN, EFMP, and EFMN all loaded most heavily on ALM.

For males, a much different pattern of loadings was evident. Again, the affective specifying variates loaded heavily on their respective factors, but we found that the variates AIKP, AIKN, CLMP, CLMN, EFMP, and EFMN also loaded heavily on the factor called perceived usefulness of mathematics.

From these models, it appears that males' general attitude toward learning mathematics is greatly accounted for by their perceived usefulness of mathematics. This is not the case for females, however. For them, it appears that their perceived usefulness of mathematics has little association with their attitude toward learning mathematics.

As for the cognitive factors included in our models, namely spatial ability, field independence/ field dependence, and flexibility of closure, they contributed very little to the variances and covariances of any of the variates in either model except for their specifying variates. There were some differences between males and females within this set of cognitive variates. For females, the flexibility of closure measures, HPT1 and HPT2, had modest loadings on the spatial ability factor. On the other hand, for males, the field independence/ field dependence measures, GEFT2 and GEFT3, had modest loadings on the spatial ability factor, and HPT1 and HPT2 had modest loadings on field independence/ field dependence. Because the weightings of the specifying variates for the cognitive variates were based on very small residual correlations with the criterion variate (FINAL), we would hesitate to make any profound conclusions about these differences.

Finally, we consider those other variates which were not used as specifying variates for any factors. These were the verbal and logical reasoning measures, VSAT, NS1, NS2, DR1, and DR2, and the locus of control measures, LCIP and LCIN. The verbal and logical reasoning variates showed no discernible pattern of loadings for females, while they loaded modestly on precalculus preparation for males. There was no discernible pattern to the loadings for LCIP and LCIN for either males or females, with very small loadings on all factors.

It must be emphasized that any conclusions or implications that we draw from these apparent sex differences in covariance structure may only be valid for the particular population observed in this study--college calculus students. Indeed, these conclusions may only be valid for college calculus students at the University of New Hampshire during the academic year 1983-1984. Also, the models developed were based on sample correlations obtained by using specific measuring instruments. A different choice of instrumentation could conceivably yield quite different results.

Implications for Educational Policy

The distinct advantage of linear covariance structural models over linear regression is that the models give us an overall picture of the relationships among all the variables involved, while linear regression concentrates on prediction of a single variable in terms of the rest. The practical value of this is best realized in terms of policy decisions that must be made in the educational arena. When one takes action to alter a variable, there can be resulting changes in many other variables which are related to the manipulated one. A good-fitting model allows us to guage these effects in ways that linear regression cannot.

Our models concerned those variables most related to mathematics achievement and participation. Since the relationships, i.e. the covariances, among these variables were statistically different for males and females, we developed separate models for males and females. What are the educational implications of the differences between the models?

Not surprisingly, academic experience and preparation are the most important factors when considering mathematics achievement and participation for both males and females, at least for these students at the level of college calculus. When academic experience and preparation have been controlled, then the most profound differences between males and females are found in the affective domain.

For males, the most important affective factor is their perceived usefulness of mathematics, since in turn, it seems closely related to their attitude toward learning mathematics in general, and their confidence and effectance motivation, in particular. For females, this perceived usefulness of mathematics seems quite independent from their other attitudes toward learning mathematics. This implies that merely alerting college women to career opportunities and the value of mathematics may not necessarily affect their confidence in learning mathematics or their general attitude toward learning mathematics, while for men, there might be such an effect. Intervention programs targeted at improving women's attitudes toward mathematics would need to do more than simply increase awareness of the value of mathematics. However, for both sexes, it appears that these affective factors play only a very small role in actually influencing future academic plans, given equal academic experience and preparation.

In summary, the models indicate that programs designed to "improve" attitudes toward mathematics, even when successful, should not be expected to automatically improve mathematics achievement or participation.

The models have strong implications for the cognitive variables, also. Because spatial ability and field independence/ field dependence are correlated with mathematics achievement and participation, a mathematics educator might be tempted to devise special programs to improve students' spatial skills through training, or to match instructional materials to cognitive style. Such spatial skill training programs could be quite effective in improving spatial skill, and such instructional materials could be developed. But our models indicate that we could not reasonably expect these actions to have anything but a miniscule effect on calculus achievement for college students with equal academic experience and preparation. There appears to be a different pattern to the loadings of cognitive variates on cognitive factors for males and females. This may be of great interest to cognitive psychologists, but the small influences of these factors on calculus achievement make them only marginally of interest to the mathematics educator concerned with improving calculus achievement.

In summary, the implications of our models for educational policy decisions are quite negative with regards to these affective and cognitive variables related to mathematics achievement and participation, at least at the level of calculus. Any policy decision to alter any of these cognitive or affective variables for college students must be made without any great expectations that a wonderful "transfer" effect will be evident in mathematics achievement and/or participation. In other words, programs designed to improve attitudes or spatial skills should have as their objectives the improvement of attitudes or spatial skills, and not a hoped-for improvement in mathematics achievement or participation. If we really want to improve mathematics achievement and participation at the college level, then we should focus on improving students' academic experience and mathematical preparation at the pre-college level. This is certainly not a new idea, but perhaps one well worth emphasizing.

Implications for Future Research

There are two directions which need to be pursued in terms of future research: 1) improvement and revision of our models, and 2) development of similar models for other populations.

While our models fit the data from the second subsample reasonably well, improvement of these models is certainly possible and should be encouraged. One place to start would be the development of better instrumentation for the factors. For example, our models indicate that academic experience and preparation were the most important factors in influencing calculus achievement for college students. We would like to focus attention on these factors in any subsequent model-building effort. Thus we might want to refine our measures of academic experience and preparation in ways that better discriminate between individuals than the simple measures that we used: grade points and pretest scores.

In the same vein, we might consider using different criterion measures. Perhaps the measure of achievement in a particular course, such as calculus, is too specific and short-sighted to use as a criterion. A more worthy criterion might be the success, or lack of it, of a student completing a degree in a technological or scientific discipline. A longitudinal study might be called for in order to gather measures of all the relevant variables at various times through the course of the student's academic career.

Our models almost certainly under-specified the cognitive factors. There seems to be good evidence that more than three factors might be necessary to explain covariances among visual skill measures of spatial ability, field independence/ field dependence, and flexibility of closure. It probably makes little sense to include measures of such variates in a model if our goal is a better understanding of mathematics achievement and participation at the college level. But, if we would shift our attention to the "visual" factors themselves, then we would certainly want to include many more and varied measures of spatial-visual skills, field independence/ field dependence, and flexibility of closure, and perhaps other cognitive measures as well.

Our models indicate that there are indeed sex differences in the covariance structure of these measures, but that these differences do little to explain differences in the covariance structure of mathematics achievement and participation measures for either male or female college calculus students. However, it may be of interest to investigate the sex differences in these measures for their own sake, apart from the mathematics achievement/participation question.

Since the most profound sex differences in covariance structure were found in the affective measures, we could concentrate more attention on the affective factors. Perhaps covariance structure differences in achievement and participation disappear when these factors are controlled. If so, then it may be appropriate to utilize discriminant analysis or some similar procedure for males and females after controlling for these factors. This may provide a future use for the algorithm Factorial Modeling is based on, since the factor extraction process controls for factors at each stage of the algorithm. We note that the affective variates in our models had the most well-defined factor structure of any set of variates for both males and females. This makes a strong case for the use of latent variable covariance structural models as a tool for understanding the relationships of these affective measures to mathematics achievement and participation.

Further investigation of how locus of control fits into the scheme of things is needed. In the present study, the scales developed as locus of control measures, LCIP and LCIN, were not nearly as reliable as the other affective measures. Our locus of control items may have been worded in ways that were too specialized for the calculus course at UNH. This, of course, might adversely affect the validity of these scales as locus of control measures. The locus of control measures were administered late in the semester, unlike the other affective measures which were administered quite early in the semester, and were thus subject to course effects that the other affective scales were not. Certainly the other affective factors made only very modest contributions to the covariances among non-affective variates in our models. Locus of control, however, might prove to have a greater influence on achievement and participation variates. What is needed is the development of multiple, highly reliable measures of locus of control for future exploratory work, with the goal of inclusion of this factor in future models.

The verbal and logical reasoning measures did not fit well in our models. This may be due to the calculus course's emphasis on computational methods. For many of the students in the course, calculus was the only required mathematics course for their academic major. It would be interesting to see if verbal and logical reasoning factors, as well as the cognitive and affective factors, might contribute more in models for achievement and participation at other levels of mathematics.

At levels of mathematics beyond the calculus, such as abstract algebra, analysis, or topology, one might expect verbal and logical reasoning abilities to play a greater role, since the emphasis shifts from computation to formal written proof. Sampling would be from a quite smaller population than that comprised of college calculus students. Comparison of such a model with the models we developed might well give some insight into what are the most important factors in determining the decision to major in mathematics.

At levels preceding calculus, at the secondary level or even the elementary level, models developed for mathematics achievement and participation might reveal a greater influence of affective and cognitive factors than we found in our models. Perhaps attitudes toward mathematics are most important when differential academic participation between the sexes is first possible-- ninth or tenth grade. Perhaps spatial ability is not an important factor for calculus achievement, but it may be for high school geometry. Such considerations suggest that separate models be developed for populations at various levels of mathematical training.

One also could argue that college calculus students form too select a population for studying sex differences in participation, since all of the students are already participating at a level of mathematics greater than most people at this age. We felt that this population was worthy of particular interest, since these students still had the fullest range of academic choices still available to them. However, it would be helpful to have models for mathematics achievement and participation for non-calculus students.

We would suggest future model-building efforts with calculus achievement and future mathematics participation in mind should concentrate on measures of academic experience, academic preparation, academic plans, and affective variables. In particular, efforts should be made to include multiple reliable and valid measures of locus of control in future exploratory work, so that the effects of this potentially important affective factor can be guaged accurately.

In terms of the methodology itself, Factorial Modeling appears to provide a practical tool for the educational researcher working in the multivariate observational setting. One area of needed research concerning FaM is the development of a statistical goodness-of-fit test for models fitted by FaM. Such work might eventually lead to the development of statistical tests of equality between parameters in the same model or different models. For example, it would have been of great interest in this study to statistically compare factor loadings pairwise between the models for males and females. More investigation regarding the use of alternative weighting schemes for specifying variates of factors is another area which might yield fruitful results.

In summary, future research is needed not only to improve on the models developed in our study, but also to develop models for other populations for comparison. With a collection of good-fitting models at our disposal, we can make more intelligent statements regarding not only which factors are most important in terms of mathematics achievement and participation, but also for whom these factors are important, and when these factors exert their greatest influence.

As our initial models become more refined and complete through these revision efforts, we may subject them to even closer scrutiny and more stringent fitting requirements by using the stronger and more complicated procedures of LISREL. In this way, we can provide stronger evidence for the plausibility (or implausibility) of these models for the covariance structure of variables related to mathematics achievement and participation.

The technique of Factorial Modeling itself warrants further investigation. This tool served the purposes of the present study quite well. Improvements and extensions of the method, as well as the development of statistical goodness-of-fit tests for FaM would be well worth pursuing.

Concluding Remarks and Summary

In this study, our approach to the investigation of individual and sex differences in mathematics achievement and participation centered on possible sex differences in covariance structure for measures representing achievement, participation, and related cognitive and affective variables. Using a sample of college calculus students, we found significant differences in the variance-covariance matrices for males and females. This led us to develop separate covariance structural models for males and females. We chose to develop models which would afford particularly unambiguous interpretations of the sources of the variances and covariances in the measures. In the language of causal modeling, we developed orthogonal factor models.

Factorial Modeling is a parameter estimation and confirmatory analysis technique for such models. Using this technique with a second sample of students, we found that our developed models fit reasonably well for both males and females. This allowed us to use these models to compare males and females for differences in covariance structure.

We found that for both male and female calculus students, academic experience and precalculus preparation were clearly the most important factors in explaining variance in calculus achievement. Affective and cognitive factors made little contribution to explaining variance in calculus achievement.

In terms of the covariance structure of the affective and cognitive variates themselves, we found evidence of a definite sex difference in the covariance structure of the affective variates, and slight differences in the covariance structure of the cognitive variates.

The educational policy implications of this study are that attempts to alter affective or cognitive variables at the level of college calculus should not be expected to result in significant changes in mathematics achievement or participation. Such attempts should be undertaken with this understanding. We emphasize that these conclusions may only be valid for the population at hand, college calculus students.

Future research and work is needed to improve on the models developed in this study, and to develop similar models for students at various levels of mathematics participation, from elementary and secondary levels to levels beyond the calculus. A collection of good-fitting covariance structural models at various levels would provide a focus for charting the development of differences in covariance structure, not only between males and females, but also between academic levels.

We conclude by saying that covariance structural modeling, along with a particular tool of that trade, Factorial Modeling, provided us with a way of investigating sex differences in mathematics achievement and participation that other researchers involved in observational educational studies should consider.

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APPENDIX

AFFECTIVE SCALES

In this section of the appendix we present the items from the various affective scales used in this study. Ten of these scales were Likert scales representing positively and negatively oriented items from attitude scales of Aiken (1963) and Fennema and Sherman (1976). The items from these scales were revised slightly to make them more appropriate for college students. The Likert scales used were:

Aiken's Revised Attitude Toward Mathematics Scale
AIKP-- 10 "positive" items from the scale
AIKN-- 10 "negative" items from the scale

Fennema-Sherman Confidence in Learning Mathematics Scale
CLMP-- 6 "positive" items from the scale
CLMN-- 6 "negative" items from the scale

Fennema-Sherman Usefulness of Mathematics Scale
PUMP-- 6 "positive" items from the scale
PUMN-- 6 "negative" items from the scale

Fennema-Sherman Mathematics as a Male Domain Scale
SMDP-- 6 "positive" items from the scale
SMDN-- 6 "negative" items from the scale

Fennema-Sherman Effectance Motivation in Mathematics Scale
EFMP-- 6 "positive" items from the scale
EFMN-- 6 "negative" items from the scale

The subjects were directed to respond to the items from these scales using the following code: A) strongly agree with the statement; B) agree with the statement; C) neutral or undecided; D) disagree with the statement; E) strongly disagree with the statement.

AIKP

1. Mathematics is very interesting to me, and I enjoy arithmetic and mathematics courses.
2. Mathematics is fascinating and fun.
3. Mathematics makes me feel secure, and at the same time it is stimulating.
4. The feeling that I have toward mathematics is a good feeling.
5. Mathematics is something that I enjoy a great deal.
6. I really like mathematics.
7. Mathematics is a course in school that I have always enjoyed studying.
8. I am happier in a mathematics class than in any other class.
9. I feel at ease in mathematics, and I like it very much.
10. I feel a definite positive reaction toward mathematics: it's enjoyable.

AIKN

1. I am always under a terrible strain in a mathematics class.
2. I do not like mathematics, and it scares me to have to take it.
3. My mind goes blank and I am unable to think clearly when working mathematics.
4. I feel a sense of insecurity when attempting mathematics.
5. Mathematics makes me feel uncomfortable, restless, irritable and impatient.
6. Mathematics makes me feel as though I'm lost in a jungle of numbers and can't find my way out.
7. When I hear the word mathematics, I have a feeling of dislike.
8. I approach mathematics with a feeling of hesitation, resulting from a fear of not being able to do mathematics.
9. It makes me nervous to even think about having to do a mathematics problem.
10. I have never liked mathematics, and it is my most dreaded subject.

CLMP

1. Generally I have felt secure about attempting mathematics.
2. I am sure I could do advanced work in mathematics.
3. I am sure that I can learn mathematics.
4. I think I could handle more difficult mathematics.
5. I can get good grades in mathematics.
6. I have a lot of self-confidence when it comes to mathematics.

CLMN

1. I'm no good in mathematics.
2. I don't think I could do advanced mathematics.
3. I'm not the type to do well in mathematics.
4. For some reason even though I study, mathematics seems unusually hard for me.
5. Most subjects I can handle O.K., but I have a knack for flubbing up mathematics.
6. Mathematics has been my worst subject.

PUMP

1. I'll need mathematics for my future work.
2. I study mathematics because I know how useful it is.
3. Knowing mathematics will help me earn a living.
4. Mathematics is a worthwhile and necessary subject.
5. I'll need a firm mastery of mathematics for my future work.
6. I will use mathematics in many ways after college.

PUMN

1. Mathematics is of no relevance to my life.
2. Mathematics will not be important to me in my life's work.
3. I see mathematics as a subject I will rarely use in my daily life after college.
4. Taking mathematics is a waste of time.
5. In terms of my adult life, it is not important for me to do well in mathematics in college.
6. I expect to have little use for mathematics when I get out of school.

SMDP

1. Females are as good as males in geometry.
2. Studying mathematics is just as appropriate for women as for men.
3. I would trust a woman just as much as I would trust a man to figure out important calculations.
4. Women can do just as well as men in mathematics.
5. Males are not naturally better than females in mathematics.
6. Women certainly are logical enough to do well in mathematics.

SMDN

1. It's hard to believe a female could be a genius in mathematics.
2. When a woman has to solve a mathematical problem, it is feminine to ask a man for help.
3. I would have more faith in the answer for a mathematical problem solved by a man than a woman.
4. Women who enjoy studying mathematics are a bit peculiar.
5. Mathematics is for men; arithmetic is for women.
6. I would expect a woman mathematician to be a masculine type of person.

EFMP

1. I like mathematics puzzles.
2. Mathematics is enjoyable and stimulating to me.
3. When a mathematics problem arises that I can't immediately solve, I stick with it until I have the solution.
4. Once I start trying to work on a mathematics puzzle I find it hard to stop.
5. When a question is left unanswered in mathematics class, I continue to think about it afterward.
6. I am challenged by mathematical problems I can't understand immediately.

EFMN

1. Figuring out mathematical problems does not appeal to me.
2. The challenge of mathematical problems does not appeal to me.
3. Mathematical puzzles are boring.
4. I don't understand how some people can spend so much time on mathematics and seem to enjoy it.
5. I would rather have someone give me the solution to a difficult mathematical problem than to have to work it out for myself.
6. I do as little work in mathematics as possible.

The locus of control scales were based on selected items from the <u>Intellectual Achievement Responsibility Questionnaire</u> developed by Crandall, Katovsky, and Crandall (1965). The abbreviations for these scales were:

LCIP-- 9 "positive" items from the scale

LCIN-- 9 "negative" items from the scale

The subjects were directed to mark either of two possible causes for a given event. One response represented an "internal" locus of control, and the other response represented an "external" locus of control. On the following pages, we indicate the "internal" response with an asterisk (*).

LCIP

1. If a grader gives you a lot of partial credit on a calculus problem, would it probably be
   (A) because he or she is an easy grader, or
   *(B) because of the work you did?

2. When you do well on a calculus exam, is it more likely to be
   *(A) because you studied for it, or
   (B) because the test was especially easy?

3. Suppose you did better than you expected in calculus. Would it probably happen
   *(A) because you tried harder, or
   (B) because someone helped you?

4. If you solve a word problem quickly, is it
   (A) because it wasn't a very hard problem, or
   *(B) because you worked on it carefully?

5. When you learn something quickly in calculus lecture, is it usually
   *(A) because you paid close attention, or
   (B) because the professor explained it clearly?

6. Suppose you became a successful engineer, scientist or doctor. Do you think this would happen
   (A) because other people helped you when you needed it, or
   *(B) because you worked very hard?

7. When you find it easy to work calculus problems, is it usually
   (A) because the problems were easy, or
   *(B) because you studied before you tried them?

8. When you remember something you heard in lecture, it is usually
   *(A) because you tried hard to remember, or
   (B) because the professor explained it well?

9. Suppose you are explaining a calculus concept to a friend and he or she learns it quickly. Would that happen more often
   *(A) because you explained it well, or
   (B) because he or she was able to understand it?

LCIN

1. When you have trouble understanding something in a calculus lecture, is it usually
   (A) because the professor didn't explain it clearly, or
   *(B) because you didn't listen carefully?

2. Suppose you want to become an engineer, scientist or doctor and you fail. Do you think this would happen
   *(A) because you didn't work hard enough, or
   (B) because you needed some help and other people didn't give it to you?

3. When you find it hard to work calculus problems, is it
   *(A) because you didn't study well enough before you tried them, or
   (B) because the problems were too hard?

4. When you forget something you heard in lecture, is it
   (A) because the professor didn't explain it very well, or
   *(B) because you didn't try very hard to remember?

5. When you don't do well on a calculus exam, is it
   (A) because the exam was especially hard, or
   *(B) because you didn't study for it?

6. If a grader gives you very little partial credit on a calculus problem, would it probably be
   (A) because he or she was a hard grader, or
   *(B) because your work wasn't good enough?

7. Suppose you don't do as well as you expected in calculus. Would this probably happen
   *(A) because you weren't as careful as you should have been, or
   (B) because you did not have enough time to devote to it?

8. Suppose you are showing a friend a calculus concept and he or she has trouble with it. Would that happen
   (A) because he or she wasn't very good at mathematics, or
   *(B) because you couldn't explain it well?

9. If you can't solve a word problem, is it more likely to happen
   *(A) because you are not especially good at doing word problems, or
   (B) because the problem wasn't written clearly enough?

EXAMPLES OF COGNITIVE MEASURES

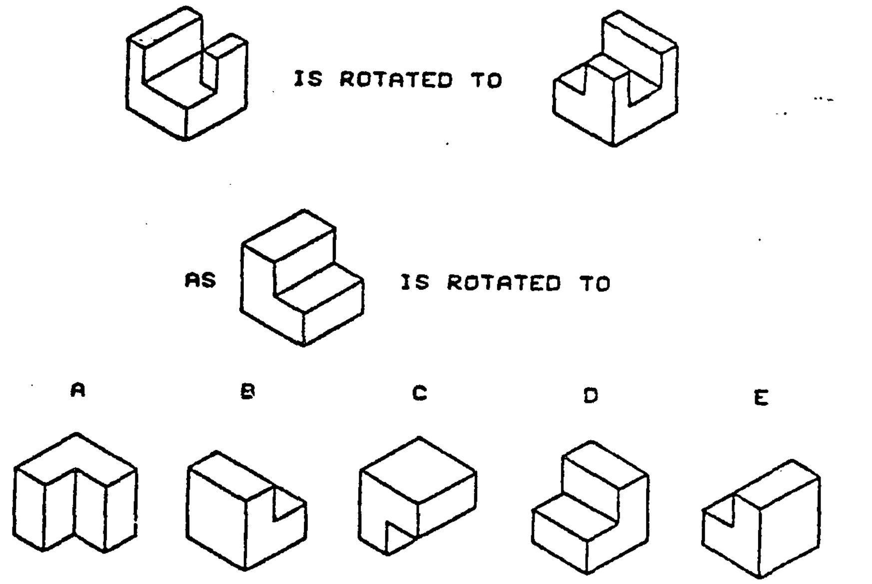
On the following pages we provide examples of the cognitive measures employed in this study. Because of copyright restrictions, we cannot reprint an example of the Group Embedded Figures Test. However, we do provide an example of a similar disembedding task-- the Hidden Figures Test from the Ekstrom, French, Harman and Dermon Kit of Factor-Referenced Cognitive Tests (1976). The examples of the Hidden Patterns Test, the Card Rotations, Nonsense Syllogisms, and Diagramming Relationships also come from the Ekstrom Kit. These examples and the examples of the Purdue Spatial Visualization of Rotations Test are reprinted with the kind permission of the Educational Testing Service and the Purdue University Research Foundation.

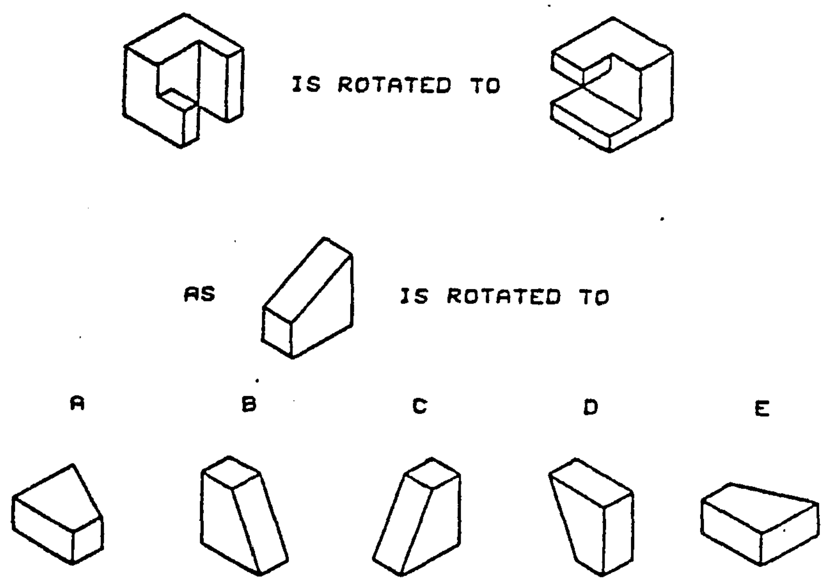
Time restrictions on the cognitive measures

Measure	Time
PSVR	none*
GEFT2, GEFT3	5 minutes each
HPT1, HPT2	3 minutes each
NS1, NS2	5 minutes each
DR1, DR2	5 minutes each
CR1, CR2	3 minutes each

*The PSVR was given with the algebra and trigonometry pretests, for which there was a total time limit of approximately one hour.

Examples of PSVR items



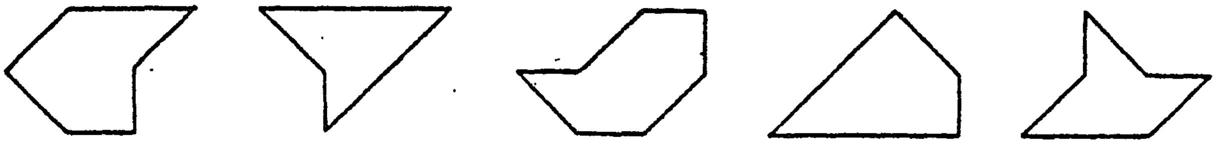


Correct answers are D and B, respectively.

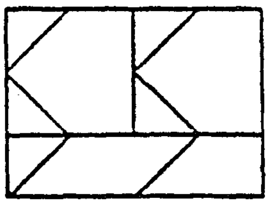
Examples from the Hidden Figures Test

NOTE: There is only one of these figures in each pattern, and this figure will always be right side up and exactly the same size as one of the five lettered figures.

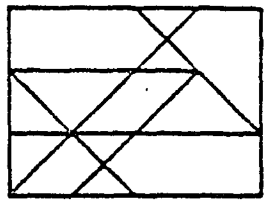
Now try these 2 examples.



A B C D E

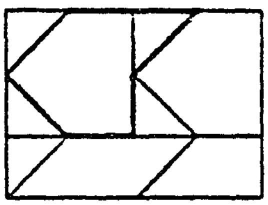
I 

A B C D E

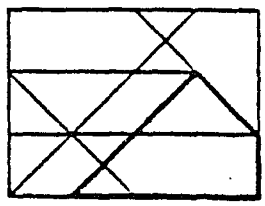
II 

A B C D E

The figures below show how the figures are included in the problems. Figure A is in the first problem and figure D in the second.

I 

~~A~~ B C D E

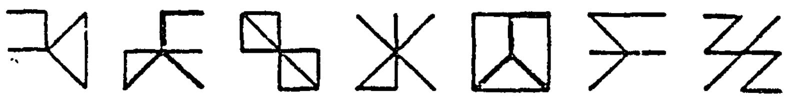
II 

A B C ~~D~~ E

Examples from the Hidden Patterns Test

The model must always be in this position, not on its side or upside down.

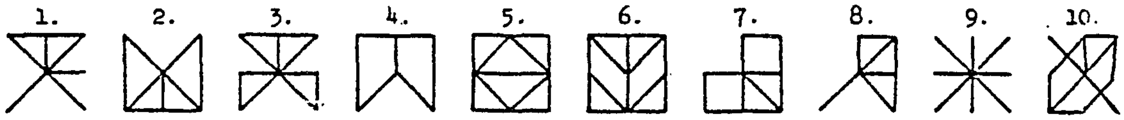
In the next row, when the model appears, it is shown by heavy lines:



(o) (X) (o) (o) (X) (o) (o)

Your task will be to place an X in the space below each pattern in which the model appears and an O below the pattern where the model does not appear. Now, try this row:

1. 2. 3. 4. 5. 6. 7. 8. 9. 10.



( ) ( ) ( ) ( ) ( ) ( ) ( ) ( ) ( ) ( )

You should have marked an X below patterns 1, 3, 4, 8, and 10, because they contain the model. You should have marked an O below patterns 2, 5, 6, 7, and 9 because they do not contain the model.

Examples of Nonsense Syllogisms

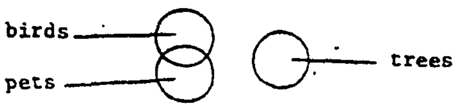
If the conclusion drawn from the statements shows good reasoning, put an X on the letter G. If the conclusion drawn from the statements shows poor reasoning, put an X on the letter P.

Now try the practice problems given below. The first two syllogisms have been correctly marked.

1)	All trees are fish. All fish are horses Therefore all trees are horses.	X	P
2)	All trees are fish. All fish are horses. Therefore all horses are trees.	G	X
3)	Some swimming pools are mountains. All mountains like cats. Therefore all swimming pools like cats.	G	P
4)	All swimming pools are mountains. All mountains like cats. Therefore all swimming pools like cats.	G	P
5)	All elephants can fly. All giants are elephants. Therefore all giants can fly.	G	P
6)	Some carrots are sports cars. Some sports cars play the piano. Therefore some carrots play the piano.	G	P
7)	No two flowers look exactly the same. Roses and tulips look exactly the same. Therefore roses and tulips are not two flowers.	G	P

The answers to the other five problems are as follows: 3 is P; 4 is G; 5 is G; 6 is P; 7 is G.

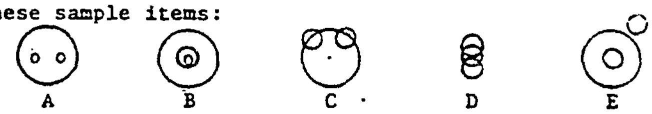
Examples of Diagramming Relationships



This diagram shows that no trees are either pets or birds, but some birds are pets and some pets are birds.

Each item in this test names three groups of things. You are to choose from the lettered diagrams at the top of the test pages the one diagram that shows the correct relationships among the three groups of things in each item. Mark the letter of the diagram that you select.

Now try these sample items:



1. Animals, cats dogs

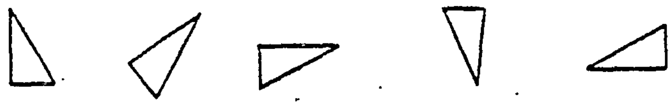
   A B C D E

2. Desks, furniture, pencils

   A B C D E

You should have marked A for 1. and E for 2.

Examples of Card Rotations



All of these drawings are of the same card, which has been slid around into different positions on the page.

Now look at the 2 cards below:

These two cards are not alike. The first cannot be made to look like the second by sliding it around on the page. It would have to be flipped over or made differently.

Each problem in this test consists of one card on the left of a vertical line and eight cards on the right. You are to decide whether each of the eight cards on the right is the same as or different from the card at the left. Mark the box beside the S if it is the same as the one at the beginning of the row. Mark the box beside the D if it is different from the one at the beginning of the row.

Practice on the following rows. The first row has been correctly marked for you.